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Essays in Climate Finance

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A thesis submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Imperial College London

February 2022

Abstract

This thesis investigates the behaviour of firms in relation to *climate-transition* events, so-called events that occur as part of the transition to a green economy to prevent climate change. The first chapter looks at the current development of the sustainable finance market to study how green securities should be optimally designed and whether measurement and information frictions can explain observed cross-sectional issuance patterns. The second chapter exploits a climate regulatory announcement to study how firms' beliefs about climate regulation affect their emissions abatement plans and how they interact with cross-firm reputation externalities. The third chapter makes use of an environmental policy implemented in the United Kingdom to study the cost-effectiveness of carbon pricing policies subject to carbon leakage risk and asymmetric information.

Declaration of originality

I herewith certify that this thesis constitutes my own work and that all material, which is not my own work, has been properly acknowledged.

Federica Zeni

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Acknowledgements

I am grateful to my supervisor, Tarun Ramadorai, whose expertise, understanding, genuine guidance and support made it possible for me to work on a topic that has become of primary interest to the society.

I am also indebted to Franklin Allen and Ansgar Walther for the great amount of help they provided me which has significantly shaped the content of this thesis.

I would like to express my personal gratitude to Savitar Sundaresan for always finding out time to help me and support me, as well as to Marcin Kacperczyk, Patrick Bolton, and all the faculty members at Imperial College Business School for their expert advice during seminars and meetings.

I dedicate my thesis to my parents, Francesca and Renato. I want to thank them for their tireless support that has given me the strength to face this challenging journey.

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Overview of the Thesis

The first chapter looks at the recent spectacular rise in issuance of *sustainability-linked loans* and *bonds*, the most prevalent types of sustainable debt instruments after *green bonds*, to study how green securities should be optimally designed to favour both the firms and the environment. The chapter develops a model of firm financing which incorporates an investor with green preferences into an otherwise standard framework of corporate financing with asymmetric information. In the model, firms seek to maximize profits by financing "green" projects or "business-as-usual" projects choosing among three contracts available: a vanilla contract, a project-based green debt contract in the spirit of green bonds, that restrict the set of projects to be financed using the proceeds but make no commitment to green outcomes, or an outcome-based green debt contract in the spirit of sustainability-linked loans and bonds, that do not impose restrictions on the use of proceeds but embed contingencies which should entail commitment to green outcomes. To match cross-sectional issuance patterns observed in the data, the model embeds a component of unverifiable moral hazard in that green outcomes can be perfectly measured only firms and can therefore be manipulated in reports. The theoretical analysis demonstrates that while outcome-based contingent green debt is unambiguously optimal under perfect market conditions, the observed co-existence of project-based and outcome-based green debt is an equilibrium result when green outcomes are manipulable and firm types differ in their ability to manipulate. Furthermore, in presence of asymmetric information about firms' type, green bonds can be used as an expensive screening device, and the empirical section shows that outcome-based contingent contracts have lower green bond premium and are issued by more emissions intensive firms.

The second chapter exploits a climate regulatory announcement to investigate the channels trough which firms' beliefs about climate regulation affect their plans of carbon emissions reduction. The study makes use of the most comprehensive dataset on self-reported corporate environmental disclosure, the Carbon Disclosure Project (CDP), to measure firms' beliefs about climate regulation, their actual carbon emissions, as well as their plans for future emissions reduction reflected in their emissions reduction targets, and attempt to rationalize the joint dynamics of those three metrics around the Paris Agreement announcement. A dynamic model of a representative firm exposed to a future carbon levy, trading-off mitigation against capital growth, facing convex abatement adjustment costs does not fit the data; but a two-firm model with cross-firm information asymmetry and reputational externalities does. Out-of-sample, the study also shows that the model predicts reversals following the US exit from the Paris agreement, revealing that abatement is strongly affected by firms' beliefs about climate regulation, and cross-firm interactions amplify the impact of regulation.

The third chapter makes use of a theoretical model and a unilateral carbon tax policy implemented in the United Kingdom to evaluate the cost-efficiency of carbon pricing policies subject to *carbon leakage* risk, the so-called risk of inefficient relocation of economic activity that results from an incomplete regulatory framework. The study develops a simple model of an imperfectly informed, budget-constrained regulator that wishes to impose a domestic carbon tax while allocating carbon subsidies to prevent relocation of the regulated firms from the domestic jurisdiction. The model predicts that in presence of relocation risk, cost-efficient subsidies should be allocated so that to equalize value-weighted marginal relocation propensities across firms. However, in line with evidence from the UK climate policy, when the regulator is imperfectly informed about determinants of relocation, subsidies follow simpler allocation rules that systematically favour emissions intensive firms. Evidence from the UK scheme shows that, over a bi-annual period following a structural change in the legislation, about half of the total carbon tax revenues are recycled into subsidies to leakage-vulnerable firms, and yet one fifth of the regulated installations exit the scheme. A quantitative exercise on the UK scheme shows that counterfactual cost-efficient targets could improve expected welfare up to 20% under the same government budget as the one actually used for the subsidies. The exercise also reveals that emissions intensive firms should not be always ranked at the highest risk of carbon leakage, and that both financial constrains and a latent factor in firms' emissions abatement are strong determinants of exit propensities.

Chapter 1

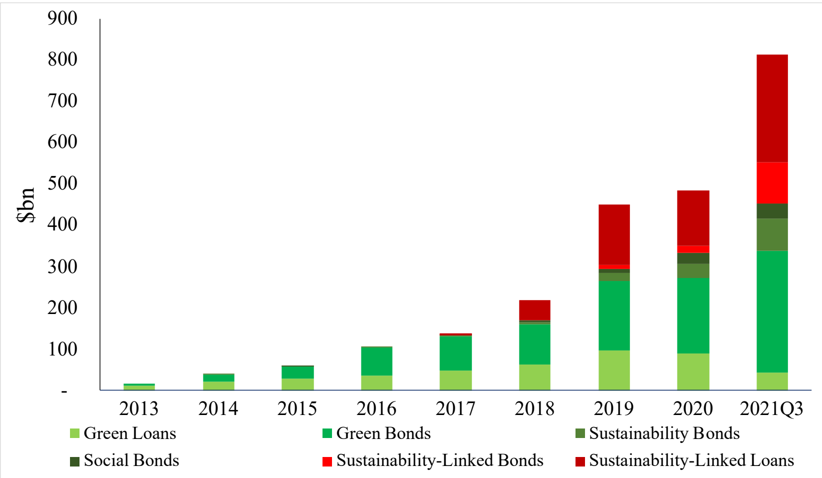
Optimal Design of Green Securities[1]

1.1 Introduction

Financial markets are playing an increasingly important role in the fight against climate change and other sustainability issues by allowing sustainability-oriented investors to finance projects that have positive environmental and social benefits. The corporate sustainable debt market opened slowly about a decade ago and has grown exponentially in recent years, reaching a cumulative volume of approximately 2.5$tn as of the third quarter of 2021.

Figure 1.1 *Corporate Sustainable Debt Market*

The figure shows cumulative issuance volume of corporate sustainable debt securities in $ billions across years. Issuance data are obtained from Bloomberg fixed income as detailed in the Appendix A.



The first and most predominant type of debt contract issued is the green bond (see Figure 1). Green

[1]This chapter is joint work with Adelina Barbalau, and adapted from the working paper *Optimal Design of Green Securities*, 2021.

bonds (GBs) are fixed income instruments which earmark proceeds for specific projects that have positive environmental and climate benefits. They are differentiated from regular bonds by a green label, which represents a commitment to exclusively use the funds raised to finance or re-finance green projects.[2] The contract focuses solely on specifying ex-ante the projects that the borrower can allocate the proceeds to, but does not embed the mechanisms needed to ensure commitment to green outcomes. In contrast, the newly emerging class of sustainability-linked loans (SLLs) and bonds (SLBs), now making up about 45% of the market, does not impose ex-ante constraints on the projects that the proceeds can be allocated to, but instead makes interest payments contingent on realized green outcomes, such as carbon emission reductions.

The introduction of contingencies in securities' payoff addresses the limitations inherent to the design of non-contingent securities such as green bonds by eliminating the need to restrict borrower's actions ex-ante and by making outcomes rather than intentions the focus of green projects financing. Importantly, this security design is in line with corporate finance theory which posits that optimal contracts should include all relevant contingencies (see, for example, Hart and Holmström [1987]). It is thus unclear why despite the successful implementation of outcome-based contingent contracts such as SLLs and SLBs, we do not observe a complete switch to contingent financing but instead, the observed market outcome points to the co-existence of contingent and non-contingent contracts.

The model we propose in this paper rationalizes observed debt issuance patterns as equilibrium outcomes of a firm financing model which embeds verifiable moral hazard, manipulation and asymmetric information. The baseline model features two time periods, an investor, and a representative firm in the market. In the first time period, the firm has access to a business-as-usual project which has a fixed cost and which will yield, in the second time period, a *certain* monetary return. In the first time period or at an interim date before the second time period, the firm can decide to upgrade to a green project. The green project yields the same monetary return as the business-as-usual project and, at some further cost, an *uncertain* green outcome, which can be conceptualised as a reduction in carbon emissions.

The investor is risk-neutral and has green preferences, in the sense that she equally values monetary

[2]In line with the ICMA standards governing the issuance of securities on the sustainable finance market, the term green refers to environmentally related outcomes, while the terms sustainability is wider and refers to environmental as well as social and potentially governance related issues.

and green outcomes.[3] We specify the green outcome delivered by the green project as the sum of a measurable and an uncertain component. The measurable component represents the firm's costly action, and can be perfectly verified by the investor at a cost. The uncertain component can only be observed by the firm at an interim date, and can be manipulated in reports at some manipulation cost.[4] The firm seeks to maximize profits by choosing to finance its investment through the issuance of one of the following three debt contract categories: a plain vanilla non-contingent contract, a project-based non-contingent green contract which involves ex-ante verification of action choices (similar in spirit to GBs), or an outcome-based contingent green contract which involves ex-post monitoring of green outcomes (similar in spirit to SLLs/SLBs).[5] The investor accepts the debt contract provided it generates at least zero return in expectation.

We first consider a model with a single firm. We show that plain vanilla contracts are affected by a moral hazard problem and can only finance business-as-usual projects, such that a specialised green finance market is needed to finance green projects. Non-contingent green contracts correct for moral hazard as they involve costly verification of actions (in the spirit of Townsend [1979]), but give rise to an opportunity cost of committing to project and action choices before learning the outcome potential of these green projects. Contingent contracts eliminate this commitment cost, but to the extent that the measurement systems on which contingencies are based can be manipulated, they are affected by a distortion discount. If the firm's distortion cost is high, we find that contingent contracts such as SLLs/SLBs are first-best. On the other hand, if the cost of distortion is low, then non-contingent contracts such as GBs become optimal.

This baseline result sheds light on the time-series evolution of the sustainable debt market and explains the initial dominance of green bonds in terms of the fact that the measurement of green outcomes was particularly difficult in the early stages of the market. On the other hand, the current co-existence of the two contract categories is the result an active trade-off between the

[3] We take as given the existence of a market that deploys capital to fund green projects (a similar assumption is also outlined in Pastor, Stambaugh, and Taylor [2020]) and focus solely on the firm's optimal debt financing choice. As far as the risk-neutrality assumption is concerned, we show in Appendix B that introducing risk-aversion does not alter the baseline predictions of the model.

[4] The measurable component can be conceptualized as the expected level of carbon emissions reduction which can be inferred from the scale of investment in the green technology. The uncertain component can be interpreted, for example, as a piece of information about the true potential of the green technology to reduce carbon emissions, that becomes subsequently known to the firm, and which the firm can manipulate.

[5] The plain vanilla non-contingent contract is the most basic form of corporate debt whereby the investor lends the money in the first time period and receives the principal plus a predefined interest rate in the second time period. Note that we focus solely on the firm debt financing problem and disregard capital structure considerations. In Appendix B we analyse the role of equity in a simple model extension which allows for uncertain monetary returns.

opportunity cost of ex-ante commitment associated with non-contingent contracts such as GBs (which arises as a correction for moral hazard), and the manipulation discount that comes with contingent contracts such as SLLs/SLBs (which arises because of measurement frictions).

Importantly, this trade-off also generates a non-monotonic relationship between the uncertainty surrounding a green project's outcome and the firm's preference for issuing a certain type of debt to finance it, which helps capturing interesting issuance patterns across industries. According to the model, projects which are more likely to be financed using non-contingent green debt are those with very high or very low levels of green outcome uncertainty. When we proxy green outcomes using carbon emissions, we see that non-contingent debt such as GBs is more prevalent in industries with either very high degree of control/measurability over carbon emissions such as utilities (because here the cost of commitment is low) or very low carbon emissions control/measurability such as financial (because here the distortion discount is very high).[6]

Next, we extend the model along the firm type dimension to explain issuance patterns within industry. Firm types are differentiated with respect to the cost of action and the cost of distortion that they face. High type firms have a higher ability to invest in green projects and do not manipulate reported outcomes, while low type firms have a higher ability to manipulate outcomes and a lower ability to take costly action to deliver green outcomes.[7]

The extended model provides testable predictions in terms of issuance choices across firm types which depend importantly on the degree of information available to the investor. When investors are perfectly informed about the firm type, the model predicts that, across possible choices of the model parameters, high firm types should always issue contingent green debt, intermediate types will issue either contingent or non-contingent green debt, whereas low firm types will issue plain vanilla debt. On the other hand, when there is asymmetric information over firm types, the model's prediction flips in that high firm types are expected to issue non-contingent green debt, whereas intermediate types will unambiguously issue contingent green debt, and low firm types continue to prefer plain vanilla debt. The intuition is that when there is asymmetric information, the investor learns something about the firm type from the financing contract proposed, and non-contingent

[6]The focus on carbon emissions as a sensible proxy for green outcome is motivated by evidence that carbon emissions represent the most common metric underlying sustainability-linked debt targets (see appendix A).

[7]We borrow this assumption from a work related to ours by Allen and Gale [1992], discussed in extent in the literature section, and test the validity of this assumption in the empirical section.

contracts such as GBs become powerful signalling devices by allowing high types to credibly reveal their ability to commit ex-ante. Since the marginal benefit of manipulation decreases with the firm type, high type firms will not find it advantageous to issue a contingent contract because by doing so they would effectively end up subsidizing low type firms.[8] Importantly, as a result of the combined presence of measurement and information frictions, the model predicts that holding an outcome-contingent green debt security should yield higher financial returns than holding a non-contingent green debt security in equilibrium, a prediction that we verify empirically.

As a first step to test the hypothesis of perfect information in the sustainable debt market, we search for ex-ante proxies of the firms' manipulation and distortion costs by merging security-level data from Bloomberg with issuer-level data from S&P Trucost and Sustainalytics. The argument is that if those proxies allow for a correct identification of firms' types within industry, then we should see that the best types, as ordered using those proxies, are the ones innovating with contingent contracts such as SLLs and SLBs. On the other hand if those proxies are only weakly correlated with unobservable characteristics of firms' types, then we should observe a negative correlation between contingent issuance choice and those noisy proxies. We measure the cost of action to deliver green outcomes using the physical cost of abating emissions as reflected in the firm's historical emissions intensity, defined as total emissions scopes per unit of the firm's assets from S&P Trucost. On the other hand, we borrow from the greenwashing literature [Netto, Sobral, Ribeiro, and Soares, 2020, Yang, 2020] and measure the cost of manipulation using the historical discrepancy between the firm's overall corporate sustainability image, as measured by the aggregate ESG score provided by Sustainalytics, and a more credible signal of environmental commitment captured by the firm's actual adoption of an Environmental Management System (EMS).[9] Regression results indicate that within industries, issuers of contingent green debt have significantly higher cost of action and significantly lower cost of manipulation, and therefore do not classify as best types following the ordering provided by our proxies, therefore supporting the presence of asymmetric information.

Finally, we test for the presence of asymmetric information by measuring yield differentials across contingent and non-contingent green debt securities after issuance. To do that, we follow the

[8]As we clarify in the paper, such flip in the equilibrium predictions relies, among other factors, on the assumption that action and distortion costs are negatively correlated across types.

[9]The EMS is a standardized framework that helps an organization achieve its environmental goals through consistent review, evaluation, and improvement of its environmental performance. A well functioning EMS both increases the firm's likelihood to achieve positive environmental outcomes and also makes it more difficult for the firm to manipulate the measurement system which monitors those outcomes (see also Lyon and Maxwell [2011]).

methodology in Zerbib [2017] and estimate green premia as the negative yield differential between a green security and a virtually identical conventional security from the same issuer. Specifically, we pair each GB, social and sustainability bond (non-contingent green debt) and SLB (contingent green debt) in our sample with a set of conventional bonds from the same issuer and with same coupon type, maturity type, currency, nearest maturity, and nearest coupon rate. After controlling for further effects due to differences in liquidity and credit ratings, we find that the green premium on non-contingent green debt is higher than the green premium on contingent green debt, although those differences are not statistically significant. This evidence appears in line with the equilibrium prediction that contingent securities are issued by lower environmental types, and should therefore compensate the investor with higher financial returns than green bonds. Put together, these empirical exercises support the joint presence of measurement and information frictions in the sustainable finance market, leading us to conclude that addressing such frictions should be a matter of first-order importance to support the transition to a green economy.

1.2 Related Literature

Our paper is related to the literature on sustainable investing,[10] which explores the condition under and channels through which financial markets can catalyze the transition to a sustainable economy. Notable papers in this literature stream include Heinkel, Kraus, and Zechner [2001] who study how exclusionary ethical investing impacts corporate behavior, Pastor et al. [2020] who study how shifts in customers' tastes for green products and investors' tastes for green holdings produce positive social impact, Oehmke and Opp [2020] who study the conditions for impact in a context in which investors can relax firms' financial constraints for responsible production, and Landier and Lovo [2020] who study how ESG funds should invest to maximize social welfare in a setup in which financing markets are subject to a search friction. A paper related to ours in this literature strand is Chowdhry, Davies, and Waters [2019] who also make the case for introducing contingencies in financing contracts. In their model, firms that cannot commit to social goals are jointly financed by profit and socially-motivated investors, and thus face a trade-off regarding which output to emphasize. In contrast to our paper, this paper has an investor focus[11] and an important

[10]There is no consensus on the terminology used to refer to investments that have non-pecuniary benefits. The terms impact, sustainable, responsible, or ESG investing tend to be used interchangeably.

[11]Among the few works that take a firm perspective there is Ramadorai and Zeni [2019] who document and rationalize corporate commitment in reducing carbon emissions around a regulatory announcement with a strategic model of reputation, and Bolton and Kacperczyk [2021] who provide an empirical analysis voluntary disclosure initiatives driven by institutional investors, and show that while institutional pressure matters, firms that respond the most are the ones that are already less carbon intensive.

role is played by the existence and behavior of groups of investors with heterogeneous beliefs and tastes regarding non-pecuniary motives. Our paper also relates to the literature on corporate green bonds, which aims at rationalizing the existence of these securities as a way to increase the firm's value by either lowering its cost of capital (Zerbib [2017]) or by signalling credible environmental commitment to investors (Flammer [2021]). We contribute to this literature by being the first to formally study corporate green bonds along with the newly emerging class of sustainability linked bonds, interpreting their co-existence as a result of measurement and information frictions.

The economic mechanisms employed in our paper are related to the literature on contract design, and in particular the literature seeking to explain missing contingencies in optimal contracts. Contract theory suggests that optimal contracts should include many contingencies that take account of all relevant information [Hart and Holmström, 1987]. A number of papers study various frictions that explain empirically observed departures from this theoretical prediction. Holmstrom and Milgrom [1991] explain missing contingencies in employment contracts in a multitask principal-agent context in which the agent allocates limited effort among competing tasks and the principal monitors these tasks with different precisions. Nachman and Noe [1994] study a capital structure problem, and use asymmetric information and adverse selection to explain the optimality of issuing debt as opposed to equity, which map into non-contingent and contingent contracts respectively. The paper most related to ours is Allen and Gale [1992], which uses measurement distortions and adverse selection to explain missing contingencies in optimal contracts in the context of a generic transaction between a buyer and a seller. Our model differs importantly in that firms themselves are not perfectly informed at the time of entering the contract, but receive complete information about their green output only at an interim date after issuance of the security. Thus, it is not only private information, but also flexibility that plays a key role in driving the results.

Finally, this paper also relates to the literature on financial innovation, which has explored a large number of reasons behind agents' incentives to innovate such as completing markets, addressing information asymmetries, responding to regulatory and economic changes, or capitalizing on investment opportunities (see Tufano [2003] for a survey). In a similar spirit to the work of Allen and Gale [1988], in our model incentives to innovate come from changes in the value of pre-existing assets or firm value.[12] In our paper, monetizing investors' green preferences depends importantly on the possibility to measure green benefits, so it is the interaction between demand for green investing and advances in measurement systems that allow firms to innovate by incorporating contingencies in their green debt contracts. A paper related to ours is Manso, Strulovici, and Tchistyi [2010] who study performance sensitive debt (PSD), an innovative debt instrument whereby the interest rate varies ex-post with some performance metric of the borrower. Despite sharing the same security payoff structure, theirs is a model model of risky debt valuation with endogenous costly bankruptcy which differs essentially from ours in that their performance metric is perfectly measurable by the investor and cannot be manipulated. Under perfect information their model predicts that PSD is sub-optimal, but when there asymmetric information between investors and the borrowing firm, PSD can be used as a screening device and so it is optimally issued by the best firm types.

1.3 Institutional Details

This section provides some institutional background behind the evolution of the corporate sustainable debt market.

The market for sustainable debt started in 2007 with the issuance of the world's first green bond by the European Investment Bank, the so called Climate Awareness Bond.[13] Green bonds (GB) are fixed income instruments which are differentiated from regular bonds by a green label, which signifies a commitment to exclusively use the funds raised to finance or re-finance green projects. Insofar as GB finance projects that are expected to yield green benefits, the capital raised depends on these expected green benefits, which are signalled ex-ante by the issuer and which effectively constitute a green promise that is monetised through the issuance of this security. Put differently, a firm issuing a green bond is basically receiving an upfront subsidy, which gives rise to an agency problem since the firm has no incentive to commit to delivering the promised green benefit once it has obtained the subsidy, given that it is costly to do so.

An effective tool to mitigate this moral hazard problem is represented by the verification process

[12] The firm innovates to maximize its value by capitalizing on the fact that investors value the green benefit that the project under management has the potential to deliver and are willing to pay for it. This is in line with the evidence that the market for sustainable financed has had a bottom up development, being driven by investor demand.

[13] The first corporate green bond was issued in 2013 by Swedish housing company Vasakronan.

associated with obtaining a green label, which is aimed at ensuring that ex-ante green promises are followed through. Issuers obtain a green label from a number of certification providers, most of which adhere to the Green Bond Principles (GBPs).[14] The GBPs provide issuers with high level guidance on the key components involved in launching a credible green bond, and place particular emphasis on ex-ante verification that all the necessary processes are in place to ensure that the proceeds will be used for the stated projects while making no reference to outcomes delivered by the projects.[15] Alongside the development of GBs, the market has seen a proliferation of debt instruments that are similar in spirit but which serve to finance other purposes, such as Social Bonds and Sustainability Bonds. While Social Bonds raise funds for projects that address social issues and/or seek to achieve positive social outcomes, the proceeds obtained through the issuance of Sustainability Bonds are dedicated to financing a combination of both green and social projects. As for GBs, there are principles to guide the issuance of Social and Sustainability Bonds, namely the Social Bond Principles (SBP) and the Sustainability Bond Guidelines (SBG), respectively.

Sustainability-linked Bonds (SLBs) and Loans (SSLs) represent new types of debt instruments which do not earmark proceeds for specific projects, but instead make the borrower's financing cost contingent on the borrower meeting specific targets, which reflect broad sustainability concerns, at predetermined dates throughout the life of the contract.[16] A firm raising capital using these state-contingent debt contracts essentially commits to making a series of interest repayments that are linked to the deviation of its realized sustainability performance from the target. The issuance of SLBs is governed by the ICMA Sustainability-Linked Bond Principles which are centred around specifying the performance targets and the ex-post reporting and verification of performance. The ex-post performance verification component is mandatory but is similar to an audit process so is less costly and less reliable compared to the ex-ante green label certification processes associated with green bonds.[17] In the case of SLLs, which represent the private debt counterpart of SLBs and whose issuance is guided by the voluntary guidelines issued by the Loan Market

[14]The GBPs, which were introduced in January 2014 by the International Capital Market Association (ICMA), are voluntary process guidelines for issuing green bonds that were put together by a consortium of some of the largest investment banks worldwide. The role of the external certification providers is to confirm that the bond align with the principles, and their services or involvement range from second party opinion to rigorous verification against standardized scientific criteria and involving the appointment of approved 3rd party verifiers. The major certification providers include the Climate Bond Initiative (CBI) Climate Bonds Certification, MSCI Green Bond Indices, Moody's Green Bond Assessment and Standard & Poor's Green Evaluations.

[15]For example, Apple clearly states that there can be no assurance" that funded projects meet investor criteria or expectations regarding sustainability performance".

[16]The first SLL was issued in April 2017 by the Dutch health technology company Koninklijke Philips.

[17]For a discussion about the difference between auditing reports and proper certifications of green securities see also the discussion in Baker, Bergstresser, Serafeim, and Wurgler [2018].

Association (LMA), ex-post reporting and verification of performance is only *recommended*, and subject to negotiation between the borrower and lenders on a transaction-by-transaction basis.

1.4 Model

The baseline economy features two time periods, an investor, and one firm in the market. At time $t = 0$, the firm has access to a project which costs 1\$ and yields a certain monetary return of \$1+R at time $t = 1$. At time $t = 0$ or at an interim date before $t = 1$, the firm can decide to upgrade to a green technology by investing in a green project. The green project delivers, at time $t = 1$, the same monetary return and an uncertain green outcome $g(\tilde{z}, a)$ which can be conceptualized as a reduction in carbon emissions. The green outcome is the sum of two components

$$g(\tilde{z}, a) = a + \sigma\tilde{z} \tag{1.1}$$

the first component a denotes the firm's costly action choice, which can be thought of as the scale of investment in the green technology, whereas the second component $\tilde{z} \sim \mathcal{N}(0, 1)$ is an uncertain state about the true environmental quality of the technology, that is revealed only to the firm at an interim date between $t = 0$ and $t = 1$. The action a encompasses the portion of the outcome that can be perfectly verified by the investor at some cost. The interpretation of this component is that based on ex-ante information about the scale of the investment in the technology, the investor can form a meaningful expectation about the average emission savings delivered by the project i.e. the action can be backed out from the cost of action, which is expressed in monetary terms and thus measurable. The uncertain state $\tilde{z}$ is the component of the outcome that cannot be observed nor verified by the investor, and that can be manipulated by the firm in reports. The interpretation is that for a given scale of investment, there is residual uncertainty with respect to the emissions savings delivered by the project, which can for instance depend on hidden technology fundamentals that are privately revealed to the firm. The parameter σ controls the level of discrepancy between the overall green outcome and its unverifiable/uncertain component.

The investor has a linear utility which equally values consumption (e.g. the monetary outcome) and the green outcome. Denoting $x = \{0, 1\}$ the firm's binary choice of whether to implement the green project, the investor's utility reads

$$\mathcal{U}^I = \mathcal{C}_0^I + \mathcal{C}_1^I + xg(\tilde{z}, a) \tag{1.2}$$

with endowments $n_0^I >> 1$ and $n_1^I = 0$ at time $t = 0$ and $t = 1$ respectively.

The firm, on the other hand, has monetary preferences only and pays a quadratic cost of action to deliver the green outcome

$$\mathcal{U}^f = \mathcal{C}_0^f + \mathcal{C}_1^f - x\frac{1}{2}\theta a^2 \tag{1.3}$$

with θ the action cost parameter, and endowments $n_0^f = n_1^f = 0$ at time $t = 0$ and $t = 1$ respectively. Before introducing the details of the financing problem, it is useful to derive an efficient benchmark for the project and investment choices of a perfectly informed social planner.

1.4.1 Central Planner Problem

The first-best project and action choices, x and a respectively, are obtained by solving the problem of a social planner, indexed by s, which is perfectly informed about the realization of the uncertain state (e.g. $\tilde{z} = z$), and maximizes the aggregate utility

$$\max_{a,x} \mathcal{U}^I + \mathcal{U}^f = R + \max_{a,x} x(g(z,a) - \frac{1}{2}\theta a^2). \tag{1.4}$$

The Euler conditions yield the following project and action choices

$$x^s(z) = 1\{\frac{1}{2}a^s + \sigma z > 0\} \quad \text{with} \quad a^s = \frac{1}{\theta}. \tag{1.5}$$

Thus, the social planner finds it optimal to implement the green project provided that the realization of the uncertain state z is such that the green outcome delivered by the project is higher than the cost. The optimal action, interpreted as the level of investment, is conditional on the project implementation and can be thought of as the intensive margin of investment. Clearly, if the project is not implemented the optimal action is zero. Importantly, note that the social planner's choices are state dependent.

1.4.2 Decentralized Problem

In the decentralized market, the firm seeks to maximize utility in (1.3) by proposing a debt contract y to the investor. The generic structure of the debt contract is as follows: at date $t = 0$, the investor lends \$1 to the firm, so that the latter can afford the implementation of (at least) the baseline project that has a positive certain monetary return.[18] Depending on the design of the

[18]The positive certain monetary return and the fact that the firm has zero endowments ensures that external financing is always profitable in equilibrium, e.g. there are no equilibrium outcomes where no contract y is chosen.

contract y and its associated characteristics, the firm will then decide the green project and action choices, x^y and a^y respectively, which depend on the realization z of the uncertain state variable $\tilde{z}$ in ways that will be detailed below. At date $t = 1$, the firm will repay the investor an amount $\$1 + \rho^y$, with ρ^y denoting the interest rate associated with the debt contract.

In what follows, we take a positive approach to studying green project financing in that we analyse the welfare implications of firm's issuance choices using a given set of debt contracts whose design is similar to that of securities currently observed in the market. Formally, we assume that the firm can choose one among a specified set of securities $y \in \{v, g, cg\}$ which vary with the interest rate specification, where v stands for a plain vanilla debt contract, g stands for a project-based non-contingent green debt contract, and cg stands for an outcome-based contingent green debt contract.

The *plain vanilla* contract, indexed by v, is the most simple form of debt contract which repays the investor at date $t = 1$ a fixed interest rate ρ^v.

The *project-based non-contingent* green debt contract, indexed by g, involves ex-ante commitment to a project $x^g = 1$ and action a^g at the moment of issuing the security. This contract specifies an interest rate ρ^g that will remain fixed throughout the life of the contract. At issuance, the firm also pays a verification cost α to certify its commitment to the project and action choices, and which can be thought of as the cost needed to allow the investor to observe the action choice a^g conditional on implementing the green project $x^g = 1$. The verification cost maps into the green bond label that certifies the firm's commitment to dedicate the proceeds to green projects, i.e. the ex-ante certification of the firm's compliance with the GBPs.

The *outcome-based contingent* green debt contract, indexed by cg, does not involve ex-ante selection of projects nor commitment to actions, but incentivize commitment to outcomes through the introduction of a state-dependent interest rate ρ^{cg} which is contingent on the realization of the uncertain green outcome:

$$\rho^{cg} = \bar{\rho}^{cg} - x^{cg} g(z_r^{cg}, a^{cg}) \tag{1.6}$$

where $\bar{\rho}^{cg}$ is a base interest rate set at date $t = 0$, x^{cg} and a^{cg} are the firm's optimal project and action choices decided at a later date after the security issuance, and z_r^{cg} is the *reported* uncertain component of the green outcome. The specification (1.6) implies that the firm will pay the base interest rate $\bar{\rho}^{cg}$ if it reports no green outcome, and it will be rewarded with a lower interest rate if it reports a positive green outcome. The firm pays an auditing cost α in order to produce the report about the green outcome $g(z_r^{cg}, a^{cg})$ and let the investor observe it.[19] Notwithstanding auditing, the reported uncertain state z_r^{cg} can differ from the true realized state z, so this specification creates an incentive for ex-post manipulation, in that by reporting a state $z_r^{cg} \geq z$, the firm can repay the debt at a lower interest rate than in the case of truthful reporting. The reported uncertain state is function of an optimal level of distortion as

$$z_r^{cg} = z + d^{cg} \tag{1.7}$$

with d distortion choice variable that comes at a quadratic cost (in the spirit of the literature on strategic communication with lying costs by Kartik [2009].

1.5 Single Firm

This section considers a single firm model to highlight the key mechanisms that drive a firm's preferences for issuing a non-contingent or a contingent debt contract. The extended model with firm types, as well as its equilibrium predictions in presence of asymmetric information are considered in the next section.

1.5.1 Plain vanilla security

It is trivial to observe that the vanilla contract is affected by a standard moral hazard problem in that costly actions to deliver the green outcome are not verified, and the contract payoff does not embed a contingency to incentivize commitment to the green outcome. As a result, any attempt to finance the green project with this security will fail, the investor will anticipate that the firm has no incentive to implement the green project upon issuance of this contract (e.g. $x^v = 0$ independently of the realized state z), and will therefore not be willing to pay a green premium by accepting a negative interest rate (e.g. the minimum contract rate would be $\rho^v \geq 0$). It is simple to show that, conditional on issuance of this contract, firm's utility reads

$$\mathcal{U}_v^f = R. \tag{1.8}$$

[19] For simplicity, we assume that auditing costs in outcome-based contingent contracts are comparable to verification costs in project-based non-contingent contracts. However, one can also show that, with exception of predictions across industries, all of the predictions outlined in this paper are the same if auditing costs are assumed strictly smaller than verification costs.

1.5.2 Project-based, non-contingent security

Project-based non-contingent green debt contracts are those whereby project selection takes place ex-ante, at security issuance and thus prior to the realization of the uncertain state affecting the green outcome. Making ex-ante project selection a defining feature of this stylised security is in line with the green bond principles, which require ex-ante specification of the use of proceeds.

We capture this in the context of our model by making the firm choose the project x^g and commit to an action choice a^g at the moment of issuing the security and thus *prior* to the realization of the random state $\tilde{z}$. Importantly, the firm pays a verification cost α to make the commitment credible. This is interpreted as the cost that the firm incurs to set up the process by which the investor will be able to verify ex-post that the action it has committed to is effectively the same as the one actually implemented. This mechanism is again in line with the green bond principles which revolve around setting up the processes and mechanisms necessary to facilitate verification, such as placing the bond proceeds in a separate account that the investor can verify to make sure that they are used for projects aligned with the security purpose.

Conditional on issuance of a debt contract g, the firm problem can be simplified as follows

$$\mathcal{U}_g^f = \max_{a,x} R - \rho^g - x\frac{1}{2}\theta a^2 \tag{1.9}$$

subject to the investor participation constraint, which features the contract specific optimal project and action choices, x^g and a^g, respectively

$$\mathbb{E}[\rho^g + x^g g(\tilde{z}, a^g)] \geq 0 \tag{1.10}$$

Recalling that with this security there is credible commitment, meaning that the project and action choices revealed at the time of issuing the security are the same as those actually implemented by the firm, i.e. $x^g = x$ and $a^g = a$, and substituting the binding participation constraint (1.10) into (1.9), the firm problem becomes

$$\mathcal{U}_g^f = R + \max_{a,x} x(\mathbb{E}[g(\tilde{z}, a)] - \frac{1}{2}\theta a^2 - \alpha) \tag{1.11}$$

from which we obtain optimal project and action choices

$$x^g = 1\{\frac{1}{2}a^g - \alpha > 0\} \text{ with } a^g = \frac{1}{\theta}. \tag{1.12}$$

From (1.10), one notes that the contract rate $\rho^g = -\mathbb{E}[x^g g(\tilde{z}, a^g)]$, from which follows that the interest rate on the project-based non-contingent contract is $\rho^g = -\frac{1}{\theta}$ if $x^g = 1$, and is $\rho^g = 0$ if $x^g = 0$. Importantly, nothing that[20]

$$\mathcal{U}_g^f > \mathcal{U}_v^f \quad \longleftrightarrow \quad x^g = 1 \tag{1.13}$$

meaning that the firm has a strict preference for contract g relative to contract v *if and only* if it commits to the implementation of a green project, then necessarily if contract g is issued, $\rho^g = -\frac{1}{\theta}$ and one expects this contract to be issued at a *lower rate* than the plain vanilla contract. This is in line with empirical evidence on the existence of a *green premium*, namely green bonds having lower yields than their plain vanilla counterparts, which increases with the credibility of the issuer [Kapraun and Scheins, 2019, Baker et al., 2018]. Thus, ex-ante commitment is important because insofar as it is credible, it provides a sufficient alignment of the firm's and the investor's incentives so that to spur the implementation of the green project. Importantly though, since the project choice is determined at issuance and therefore independent of the realisation of the random state z, ex-ante commitment is also costly as the firm gives up the opportunity to wait and learn more about the green technology. This is a first important implication of the model stating that, when resolving the moral hazard problem intrinsic in the plain vanilla contract by means of another (green) non-contingent contract, there are some inefficiencies related to the fact that the firm is forced to make green promises at issuance.

1.5.3 Outcome-based, contingent security

With contingent green debt contracts, the firm does not commit to projects ex-ante, but chooses them ex-post after the issuance of the security and thus after the observation of the random state $\tilde{z}$. With this security, instead of ex-ante commitment we have ex-post reporting of realised green outcomes, which can be manipulated.

[20]This follows from the fact that the firm's utility if $x^g = 1$ is $\mathcal{U}_g^f = R + \frac{1}{2\theta} - \alpha$ and this is greater than $\mathcal{U}_v^f$ if $2\alpha\theta < 1$, which is exactly the condition for $x^g = 1$. On the other hand, if $x^g = 1$ the firm utility is $\mathcal{U}_g^f = R = \mathcal{U}_v^f$.

The firm problem upon issuance of this contract can be simplified to

$$\mathcal{U}^f_{cg} = R - \bar{\rho}^{cg} + \max_{a,x,d} x(g(z_r, a) - \frac{1}{2}\theta a^2 - \frac{1}{2}\psi d^2 - \alpha) \tag{1.14}$$

where ψ is a distortion cost parameter, α is the cost of auditing and the base interest rate is now subject to the participation constraint

$$\bar{\rho}^{cg} \geq \mathbb{E}[x^{cg} g(\tilde{z}^{cg}_r, a^{cg}) - x^{cg} g(\tilde{z}, a^{cg})]. \tag{1.15}$$

The participation constraint tells us that the base rate $\bar{\rho}^{cg}$ is at least as high as the expected distortion imposed by the firm. Specifically, the minimum acceptable base interest rate $\bar{\rho}^{cg}$ reflects the expected deviation of reported green outcome from the actual green outcome of the project, such that the investor effectively imposes a *distortion discount* in the pricing of this contract by raising the expected cost of financing for the firm.

When the cost of distortion is prohibitively high $\psi = +\infty$ such that $d^{cg} = 0$, the green outcome is truthfully reported $z^{cg}_r = z$ for each realization z of the uncertain state $\tilde{z}$. The minimum required interest rate $\bar{\rho}^{cg}$ is thus zero and the variable, state-contingent interest rate ρ^{cg} in (1.6) will depend on the reported green outcome; specifically, it will be set so as to perfectly offset the reported green performance across each state z. Making explicit the dependence on the realised state z, first-order conditions yield optimal choices

$$x^{cg}(z) = 1\{\frac{1}{2}a^{cg} + \sigma z - \alpha > 0\} \text{ with } \; a^{cg} = \frac{1}{\theta}. \tag{1.16}$$

The firm's utility in this case is

$$\mathcal{U}^f_{cg} = \mathcal{U}^f_v + \Big(\frac{1}{2}\frac{1}{\theta} + \sigma\tilde{z} - \alpha\Big)^+ \tag{1.17}$$

and its expected value is unambiguously higher than $\mathcal{U}^f_v$, as well as unambiguously higher than $\mathcal{U}^f_g$, as formalized in Appendix B. In fact, note that if manipulation is prohibitively costly and auditing costs are low, the optimal state-dependent choices equate the first best in (1.5).

On the other hand when the distortion cost $\psi << +\infty$, meaning when the contingency depends on a measurement system which can be manipulated, action and distortion choices read

$$x^{cg}(z) = 1\{\frac{1}{2}a^{cg} + \frac{\sigma}{2}d^{cg} + \sigma z - \alpha > 0\} \text{ with } \; a^{cg} = \frac{1}{\theta} \text{ and } d^{cg} = \frac{\sigma}{\psi}. \tag{1.18}$$

Result (1.18) states that when manipulation is possible, the firm's optimal distortion d^{cg} increases with the uncertainty of the project green outcome σ and decreases with the distortion cost ψ.[21] Importantly, note that the firm may optimally spend more in distortion than in actual investment if the model parameters satisfy $\theta > \frac{\psi}{\sigma}$. This prediction implies that firms can achieve a higher reported level of green benefits by manipulating the reported green outcome of projects with a hard-to-assess impact instead of investing in costly projects with a measurable impact. This model feature speaks to the documented practice of *greenwashing*, discussed in more detail in the empirical section, which consists of engaging in selective disclosure and manipulative practices in order to inflate perceived sustainability performance.

Equation (1.18) also indicates that because of a state-independent gain that comes from manipulation, a green project is unambiguously *more* likely to be implemented when manipulation is possible than in the case of no manipulation. This is an important feature of the model which implies that, for high levels of manipulation, the benefit of waiting to learn the uncertain state z is eroded by the possibility of manipulation. On the other hand, as reported in Appendix B, the optimal expected green outcome under manipulation lies between the outcome obtained using the non-contingent green security g, and that obtained using the contingent green security cg with no manipulation.

Plugging in optimal choices into the firm utility we have

$$\mathcal{U}^f_{cg} = \mathcal{U}^f_v + (\frac{1}{2}\frac{1}{\theta} + \frac{1}{2}\frac{\sigma^2}{\psi} + \sigma\tilde{z} - \alpha)^+ - \bar{\rho}^{cg}. \tag{1.19}$$

Note that if the minimum required rate $\bar{\rho}^{cg}$ was set to zero, then the firm would have a higher expected return relative to the case of no manipulation. However, the investor is aware that the reported green outcome is different from the actual green outcome, and so will require a higher

[21] This derives from the fact that the cost of distortion is independent of σ, hence distortion benefits increase with σ. A different specification where the distortion costs increase linearly in σ does not affect qualitatively any of the predictions in the paper.

base interest rate

$$\bar{\rho}^{cg} = \mathbb{E}[\frac{\sigma^2}{\psi}1\{\frac{1}{2}\frac{1}{\theta} + \frac{1}{2}\frac{\sigma^2}{\psi} + \sigma\tilde{z} - \alpha > 0\}] \tag{1.20}$$

which is given by plugging in the optimal distortion choice in (1.18) into (1.15). In other words, we assume that the investor is perfectly internalizing the distortion imposed by the firm by setting the base rate to satisfy the participation constraint outlined in (1.15).

As we show next, when the green outcome is manipulable and the investor correctly internalizes this, the firm's expected utility when financing is done using the contingent security is no longer unambiguously higher than that obtained when issuing non-contingent contracts.

1.5.4 Optimal security choice

Formally, the firm's contract choice can be written as

$$y = argmax_{v,g,cg}\{\mathcal{U}_v^f, \mathcal{U}_g^f, \mathbb{E}[\mathcal{U}_{cg}^f]\} \tag{1.21}$$

where $\mathcal{U}_v^f$,$\mathcal{U}_g^f$ and $\mathbb{E}[\mathcal{U}_{cg}^f]$ denote the firm's expected utility upon issuance of the plain vanilla contract v, the non-contingent green contract g, and the contingent green contract cg respectively.

Trade-off driving choice between contingent and non-contingent green debt contracts. Let's assume for a moment that the fixed cost $\alpha = 0$, so that the firm is strictly better off issuing one of the proposed green debt contracts and not the plain vanilla one. There are two competing forces which drive the firm's preference for a contingent green contract relative to a non-contingent green contract: the *opportunity cost* of committing to projects ex-ante associated with the non-contingent contract, and the *distortion discount* generated by the fact that reported outcomes can be manipulated associated with the contingent contract. These competing forces are identified in equation (1.22) by adding and subtracting the firm's utility from the issuance of a synthetic *project-based contingent green* contract pcg, that is a contingent contract which embeds the incentive to manipulate as in cg, but which also involves ex-ante selection of the green project at issuance as in g,[22] so that net profits can be decomposed as

$$\mathbb{E}[\mathcal{U}_{cg}^f] - \mathcal{U}_g^f = \underbrace{(\mathbb{E}[\mathcal{U}_{cg}^f] - \mathbb{E}[\mathcal{U}_{pcg}^f])}_{\text{opportunity cost} \geq 0} - \underbrace{(\mathcal{U}_g^f - \mathbb{E}[\mathcal{U}_{pcg}^f])}_{\text{distortion discount} \geq 0} \quad . \tag{1.22}$$

[22]One can easily show that $\mathbb{E}[\mathcal{U}_{pcg}^f] = \mathcal{U}_v^f + \frac{1}{2}\frac{1}{\phi} - \frac{\sigma^2}{2}\frac{1}{\psi}$.

It is therefore immediate to see that, if the *opportunity cost* of committing ex-ante to the green project is lower than the *distortion discount* generated by manipulation, then the firm should opt for the non-contingent green security g, whereas if the opposite is true than the firm should opt for the contingent green security cg.

Figure 1.2 *Comparative Statics of the Trade-Off - Single Firm*

The plots show the firm's expected net profits in (1.22) (black line) as well as the opportunity cost component (green line) and distortion cost component (red line) as a function of the parameter $\sigma \in [0, 2]$ (left plot), $\theta \in [0.5, 10]$ (mid plot), and $\psi \in [1, 50]$ (right plot) respectively. Other model parameters are $\alpha = 0.0$, $\phi = 1.5$, $\psi = 1.8$ (left plot), $\alpha = 0.0$, $\psi = 2.0$, $\sigma = 0.5$ (right plot), $\alpha = 0.0$, $\phi = 1.0$, $\sigma = 0.5$ respectively.

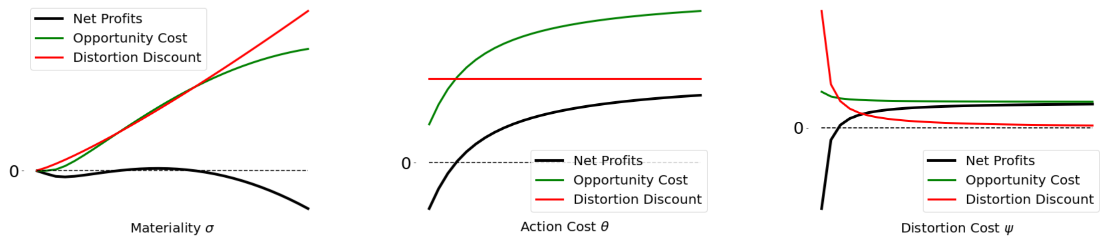


Figure 1.2 shows how the trade-off in (1.22) varies with the uncertainty σ (left-hand plot), the action cost θ (mid plot), and the distortion cost ψ (right-hand plot) respectively. The left-hand plot shows that preferences are non-monotonic as a function of the uncertainty parameter σ. As σ increases, then both the opportunity cost of commitment (in green) as well as the distortion discount (in red) increase as a function of σ.[23] However, one notes that the distortion discount is convex in σ, whereas the opportunity cost of commitment is first convex and then concave in σ. The convexity of the distortion discount comes from the fact that the expected level of distortion in a green project (or equivalently the base rate in (1.20)) is quadratic in σ. On the other hand, the convexity and then concavity of the opportunity cost of commitment requires more explanation: for small values of σ, expected benefits from manipulation are low and the firm's compensation is largely dependent on the *true* outcome state z. In such a case, an increase in σ increases the "value of the option to wait" in the standard quadratic manner[24], generating the observed convexity. On the other hand when σ becomes larger, expected benefits from manipulation become a predominant portion of the firm's compensation, therefore inducing the firm to undertake the green project

[23] Note that for fully material activities (i.e. $\sigma = 0$) the firm is always indifferent between a contingent and a non-contingent contract because the opportunity cost of committing to a project ex-ante is equal to the ex-post distortion discount, and both are equal to zero.

[24] See, for example, **?**.

independently of the realized outcome state z. As a result of these combined non-linearities, the firm tends to prefer non-contingent green contracts when σ is low, contingent green contracts for intermediate values of σ, and it eventually opts for the non-contingent green contracts when σ is large. As we show later in the empirical section, this interesting non-monotonicity result is in line with observed issuance patterns across industries.

The mid plot shows that net profits from issuance of the contingent contract increase monotonically with the action cost θ and are uniquely driven by the opportunity cost component. Specifically, the opportunity cost of foregoing information about the green outcome increases as the predictable component of the green outcome (i.e. the inverse of the cost of action θ) decreases. As we argue later when introducing firm types, this feature is relevant in generating equilibrium results that vary considerably depending on the investor's information set. Similarly, the right-hand plot shows that net profits from issuance of the contingent contract increase monotonically with the distortion cost ψ and they are (almost) uniquely driven by the distortion discount component. Importantly as formalized by the proposition below, for extreme values of the distortion discount ψ, the firm has a strict preference for the non-contingent contract or for the contingent contract, in the sense that it is a strictly dominant strategy for the firm to finance the green project via one or the other type of contract independently of the other model parameters.

Proposition 1. *Let y denote the optimal contract choice in* (1.19). *For each couple of parameters $(\sigma, \theta) \in (0, +\infty)$ and $\alpha \geq 0$, it always exists a pair $(\underline{\psi}, \overline{\psi})$ such that:*

- *if the distortion cost $\psi > \overline{\psi}$, then $y = cg$ and the firm always issues a contingent contract.*
- *if the distortion cost $\psi < \underline{\psi}$, then $y \neq cg$ and the firm never issues a contingent contract.In such a case, if $2\alpha\theta > 1$, then $y = v$ and the firm issues a plain vanilla contract, whereas if $2\alpha\theta \leq 1$, then $y = g$ and the firm issues a non-contingent green contract.*

This baseline proposition sheds light on the time-series evolution of the sustainable debt market and explains the initial dominance of green bonds in terms of the fact that the measurement of green outcomes was particularly difficult in the early stages of the market (e.g. when $\psi < \underline{\psi}$). On the other hand, when green outcomes becomes measurable with great precision (e.g. when $\psi > \overline{\psi}$), then the model predicts that the outcome-contingent contract is unambiguously optimal.

1.6 Multiple Firm Types

So far we have focused on optimal security issuance from the point of view of a single firm, deriving predictions in a general setting which depends on three independent state variables: the cost of action, the cost of distortion, and the uncertainty of the project outcome. In this section we aim to impose restrictions on the firm's action and distortion technology so as to reduce the number of state variables at play and derive more refined, testable predictions from the model.

We assume that there is a continuum of firm types k drawn from a uniform distribution $k \sim \mathcal{U}[0, 1]$. The firm type k is related with the cost of action and the cost of distortion parameters as follows

$$\theta_k = \phi \frac{1}{k}, \quad \psi_k = \psi \frac{1}{1-k} \tag{1.23}$$

meaning that the highest type firm, $k = 1$, has infinite distortion cost and action cost equal to θ, while the lowest type firm, $k = 0$, has infinite action cost and distortion cost equal to ψ. The pair (θ_k, ψ_k) identifies the firm type and is independent of the parameter σ, which now uniquely identifies the project type in terms of green outcome uncertainty.

Condition (1.23) states that the ability to distort the green outcome is *negatively correlated* with the ability to produce the outcome in the first place. Intuitively, the assumption implies that it is often companies that do not have systems in place to measure negative externalities/green outcomes that both: 1) have leeway to misreport or manipulate, i.e. have low cost of distortion; and 2) do not take action to reduce negative externalities/deliver green outcomes, i.e. have high cost of action. This assumption is also supported by definition that the Environmental Protection Agency (EPA) gives to an Environmental Management System (EMS), namely "*[..] a framework that helps an organization achieve its environmental goals through consistent review, evaluation, and improvement of its environmental performance. The assumption is that this consistent review and evaluation will identify opportunities for improving and implementing the environmental performance of the organization*". While the adoption of an EMS stands for commitment to environmental performance, Lyon and Maxwell [2011] also find that corporate adoption of an EMS also makes it more difficult for the firm to manipulate the measurement system which monitors those outcomes. These lend support to the idea that the propensity to take costly action is negatively related to the propensity to manipulate.

In deriving the predictions that follow, we assume that the verification costs α satisfies $0 < 2\alpha\theta < 1$ for a given action cost θ, so that the issuance of the project-based non-contingent green contract has positive (negative) net present value for the highest (lowest) type $k = 1$ ($k = 0$).[25]

1.6.1 Perfect Information

We first analyse the baseline case where the investor is perfectly informed about the firm type k, that is, the continuum of firm types k can be perfectly observed by the investor.

Optimal security choice

A firm k's contract choice is

$$y_k = argmax_{v,g,cg}\{\mathcal{U}_v^f, \mathcal{U}_g^f(k), \mathbb{E}[\mathcal{U}_{cg}^f(k)]\} \tag{1.24}$$

where $\mathcal{U}_g^f(k)$ and $\mathbb{E}[\mathcal{U}_{cg}^f(k)]$ are type-specific utilities from issuance of the non-contingent green contract g and the contingent green contract cg obtained substituting the expressions for θ_k and ψ_k in (1.23) into the utility functions (1.11) and (1.19), respectively.[26]

The expected net profits from issuing the contingent contract cg are defined as

$$\begin{cases} \mathbb{E}[\mathcal{U}_{cg}^f(k)] - \mathcal{U}_v^f & \text{if } \ k \in [0, 2\alpha\theta] \\ \mathbb{E}[\mathcal{U}_{cg}^f(k)] - \mathcal{U}_g^f(k) & \text{if } \ k \in (2\alpha\theta, 1]. \end{cases} \tag{1.25}$$

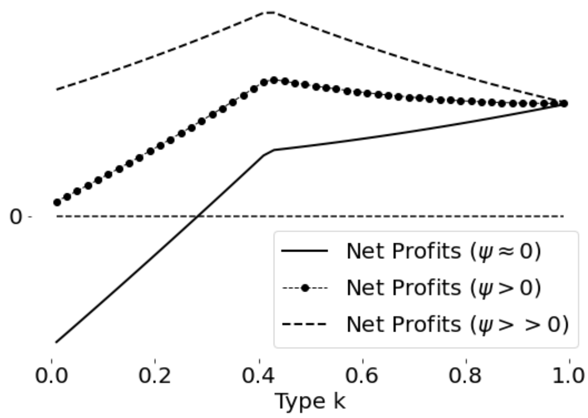
Figure 1.3 shows that if $k \in [0, 2\alpha\theta]$, then the net profits in (1.25) are strictly increasing as a function of the type k. This is because when the alternative is a plain vanilla contract, higher types are better off issuing contingent contracts because of their combined lower action costs and higher distortion costs. On the other hand, when $k \in (2\alpha\theta, 1]$, then the net profits in (1.25) can be non-monotonic as a function of k depending on the magnitude of the type-specific opportunity cost of ex-ante commitment relative to the manipulation discount. Specifically, the opportunity cost of ex-ante commitment decreases monotonically in k as the action cost θ_k decreases, making contingent contracts progressively *less* appealing for the higher type. On the other hand, the

[25] The condition $0 < 2\alpha\theta < 1$ comes from the firm utility associated with the non-contingent green contract which for the firm type k reads $\mathcal{U}_g^f(k) = \mathcal{U}_v^f + \frac{k}{2\theta} - \alpha$, such that the non-contingent green contract is strictly preferred if and only if $k > 2\alpha\theta$. Thus, there is an internal type $k = 2\alpha\theta \in (0, 1)$ which is indifferent between issuing the plain vanilla and the green non-contingent contract.

[26] Explicit expressions for these utilities can be found in Appendix B.

Figure 1.3 *Comparative Statics of the Trade-Off - Multiple Firm Types*

The plot shows the firm's net expected profits from issuance of a contingent contract as a function of the firm type k in (1.25) for three different values of the distortion cost $\psi = 0.7$ (thick line) $\psi = 1.2$ (dotted line) and $\psi = 9$ (dashed line) respectively. Other model parameters are $\theta = 0.7$, $\alpha = 0.3$, $\sigma = 1.0$.



manipulation discount also decreases monotonically in the type k as the cost of distortion ψ_k increases, making contingent contracts progressively *more* appealing for the higher type. Depending on the magnitude of ψ relative to θ, either of the terms prevails making net profits from issuance of the contingent contract increasing, decreasing, or non-monotonic as a function of the firm's type. Importantly though, as long as $\sigma \in (0, +\infty)$, the highest types *always* issue the contingent contract across all values of distortion cost $\psi \in (0, +\infty)$ and action cost $\theta \in (0, +\infty)$,[27] the lowest types can either issue contingent contracts or plain vanilla contracts,[28] whereas intermediate types can issue a combination of contingent and non-contingent green debt. More formally, we prove in Appendix B the following

Proposition 2. *Let y_k denote the optimal contract choice that maximizes the firm problem in* (1.29) *for a type $k \in [0, 1]$ with action and distortion costs that vary as in* (1.23)*. Then for a given triple of parameters $(\theta, \sigma, \psi) \in (0, \infty)$ and verification cost α such that $0 < 2\alpha\theta < 1$, there exists two types $\underline{k} \leq \overline{k}$ such that*

- *if $k \geq \overline{k}$ then $y_k = cg$ the firm issues a contingent green contract.*
- *if $k \leq \underline{k}$ then $y_k = v$ and the firm issues a non-contingent plain vanilla contract.*
- *if $\underline{k} < k < \overline{k}$ then either $y_k = g$ and the firm issues a non-contingent green contract, or*

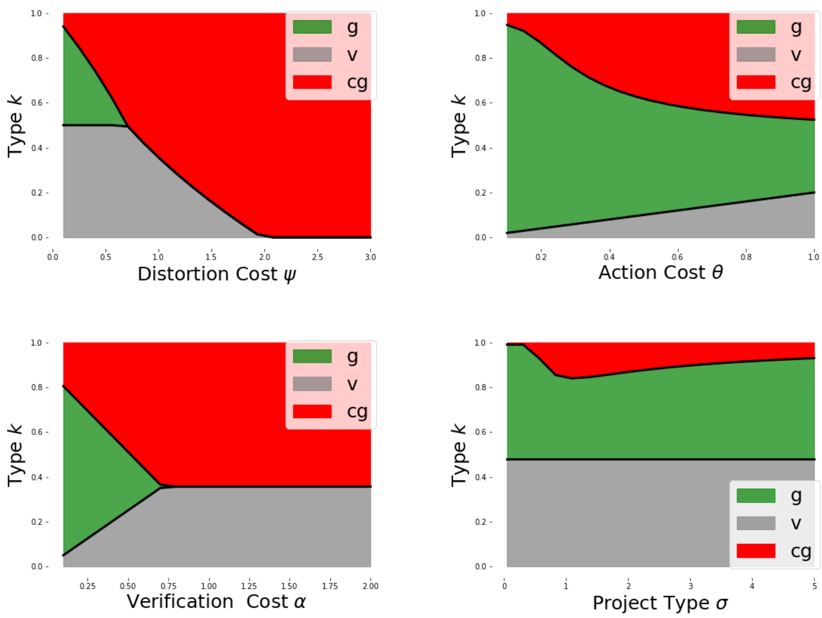
[27]This follows from Proposition 1 and from the specification of the distortion cost function across types.
[28]This follows from the assumption that $0 < 2\alpha\theta < 1$.

there exists an intermediate cutoff type $k^{'}$ such that if $\underline{k} < k < k^{'}$ then $y_k = cg$, whereas if $k^{'} < k < \overline{k}$ then $y_k = g$.

Figure 1.4 shows how the optimal issuance strategies vary as a function of the distortion cost ψ, the action cost θ, the verification cost α and the uncertainty σ. The figure illustrates that on average across possible choices of the parameters, higher types are more likely to issue the contingent green contract (red region), intermediate types are more likely to issue the non-contingent green contract (green region), whereas lower types are more likely to issue the plain vanilla non-contingent contract (grey region).[29] It is interesting to note that, as discussed earlier for the single-firm case, preferences for the contingent contract are on average higher for projects with intermediate level of uncertainty (bottom right-hand plot in Figure 1.4).

Figure 1.4 *Equilibrium Contract Choice - Perfect Information*

The plots show the firm's optimal contract choice as a function of the type k (y-axis) and the parameters ψ, θ, α, and σ respectively. Model parameters are $\theta = 0.25$, $\alpha = 1.0$, $\sigma = 2.0$ (top left plot), $\alpha = 0.1$, $\psi = 1.0$, $\sigma = 2.0$ (top right plot), $\theta = 0.25$, $\psi = 1.0$, $\sigma = 2.0$ (bottom left plot), and $\theta = 0.4$, $\alpha = 0.6$, $\psi = 0.3$ (bottom right plot) respectively.

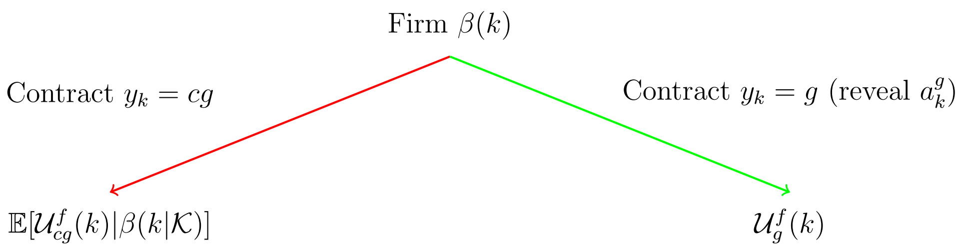


[29] As we outline in detail in the Appendix B, it may exist a region of the model parameters where the issuance strategy $y_k = cg$ is non-monotonic in k. However, such region is very small and not attained for any of the parameters choices reported in Figure 1.2.

1.6.2 Asymmetric Information

In this section we elaborate the model further in that we assume that there is asymmetric information over the firm's type k, meaning that the investor cannot observe the atomistic type k but only knows whether the firm is "good enough" so that it could afford issuing a green debt contract of either the contingent or non-contingent type (i.e. $k \in (2\alpha\theta, 1]$), or if it can only opt for the plain vanilla contract as an alternative to contingent green debt (i.e. $k \in [0, 2\alpha\theta]$). We choose this specification as it allows for an intuitive and tractable equilibrium result. Furthermore, we believe that it is plausible to assume that the investor holds a certain degree of information about the environmental quality of the firm, though the information is imperfect. In Appendix B, we also consider the case of full asymmetric information where the investor only knows that $k \sim \mathcal{U}[0, 1]$.

The game tree below summarizes the signalling game for a firm that is evaluating the best among the available green debt contracts. The first mover is the firm, which can belong to a continuum of types $k \in (2\alpha\theta, 1]$ and has two financing strategies, namely to issue a contingent green or a non-contingent green debt contract $y_k = \{cg, g\}$. The second mover is the investor, which has prior belief over the firm's type given by the distribution function $\beta(k) \sim \mathcal{U}(2\theta\alpha, 1]$.[30]



The right branch of the tree shows that if the firm proposes a non-contingent contract g, then it will attain the type-specific utility $\mathcal{U}_g^f(k)$. Specifically, through ex-ante commitment to actions a_k^g, the non-contingent green contract g allows the investor to perfectly infer firm's type k at issuance, and therefore to update its prior belief $\beta(k)$ from a distribution function to the atomistic type k. On the other hand, the left branch shows that, if the firm proposes a non-contingent contract cg, then it will attain an expected utility which is conditional to the group of firms that are issuing this contract, denoted $\mathcal{K} := \{k \in (2\alpha\theta, 1] \ s.t. \ y_k = cg\}$. More specifically, the investor's posterior

[30] Note that in principle, the investor has also two strategies, which is to either buy or refuse the proposed contract y_k. However, since for the firm is a strictly dominant strategy to issue at least one contract among $\{v, g, cg\}$ (this because $\min\{\mathcal{U}_v^f, \mathcal{U}_g^f(k), \mathbb{E}[\mathcal{U}_{cg}^f(k)]\} \geq R > 0$), we can already exclude an equilibrium outcome where the investor refuses the contract and focus on the simplified signalling game described in the graph.

belief after observing this issuance choice follows the distribution function $\beta(k|\mathcal{K}) \sim \mathcal{U}[\mathcal{K}]$, and each firm $k \in \mathcal{K}$ receives a group-specific interest rate

$$\bar{\rho}_{\mathcal{K}}^{cg} = \int_{2\alpha\theta}^{1} \bar{\rho}_{k}^{cg} \beta(k|\mathcal{K}) dk \tag{1.26}$$

which differs from the type-specific rate $\bar{\rho}_k^{cg}$ obtained plugging ψ_k and θ_k into (1.20). A firm k's expected utility from issuing the contract cg conditional on the investor's posterior belief is then expressed as

$$\mathbb{E}[\mathcal{U}_{cg}^{f}(k)|\beta(k|\mathcal{K})] = \mathbb{E}[\mathcal{U}_{cg}^{f}(k)] + \bar{\rho}_{k}^{cg} - \bar{\rho}_{\mathcal{K}}^{cg}. \tag{1.27}$$

From the expression in (1.27), one can intuitively anticipate that asymmetric information skews the firm's preferences for issuing contingent contracts towards lower types k. This is because the minimum required interest rate increases with expected distortion, and the latter decreases with firm type k. Consequently, lower types (those below the average type in group $\mathcal{K}$) are receiving a lower rate than the benchmark case with perfect information, i.e. $\bar{\rho}_{\mathcal{K}}^{cg} < \bar{\rho}_{k}^{cg}$ such that $\mathbb{E}[\mathcal{U}_{cg}^{f}(k)|\beta(k|\mathcal{K})] > \mathbb{E}[\mathcal{U}_{cg}^{f}(k)]$, whereas higher types (those k above the average type in group $\mathcal{K}$) are receiving a higher rate than the benchmark case with perfect information, i.e. $\bar{\rho}_{\mathcal{K}}^{cg} > \bar{\rho}_{k}^{cg}$ such that $\mathbb{E}[\mathcal{U}_{cg}^{f}(k)|\beta(k|\mathcal{K})] < \mathbb{E}[\mathcal{U}_{cg}^{f}(k)]$. Effectively, by issuing the contingent green contract, higher types contribute to lowering the average group-specific rate and thus end up subsidising lower types.

We first introduce the following

Perfect Bayes Equilibrium (PBE) For a given $\mathcal{K}$, the pair $(y_k, \beta(k|\mathcal{K}))$ such that

$$y_k : \begin{cases} = cg \quad if \quad k \in \mathcal{K} \\ = g \quad if \quad k \notin \mathcal{K} \end{cases} \tag{1.28}$$

and the investor's posterior belief $\beta(k|\mathcal{K}) \sim \mathcal{U}[\mathcal{K}]$ is a PBE if it verifies

$$y_k = argmax_{v,g,cg}\{\mathcal{U}_v^f, \mathcal{U}_g^f(k), \mathbb{E}[\mathcal{U}_{cg}^f(k)|\beta(k|\mathcal{K})]\} \tag{1.29}$$

for each $k \in (2\alpha\theta, 1]$.

Then, we prove in Appendix B the following

Proposition 3. *If $\theta < \frac{\psi}{\sigma^2}$ is verified, then for each $k \in (2\alpha\theta, 1]$, it holds that*

$$\frac{\partial}{\partial k}\mathbb{E}[\mathcal{U}^f_{cg}(k)|\beta(k|\mathcal{K})] - \mathcal{U}^f_g(k) \leq 0 \tag{1.30}$$

where $\mathcal{K} = [2\alpha\theta, k)$ and the following PBE are possible

- $\mathcal{K} = \emptyset$, *in which case $y_k = g$ for each $k \in (2\alpha\theta, 1]$.*
- $\mathcal{K} = (2\alpha\theta, 1]$, *in which case $y_k = cg$ for each $k \in (2\alpha\theta, 1]$.*
- $\mathcal{K} = [2\alpha\theta, e]$ *for $e < 1$, in which case $y_k = cg$ for $k \in [2\alpha\theta, e]$, whereas $y_k = g$ for $k \in (e, 1]$.*

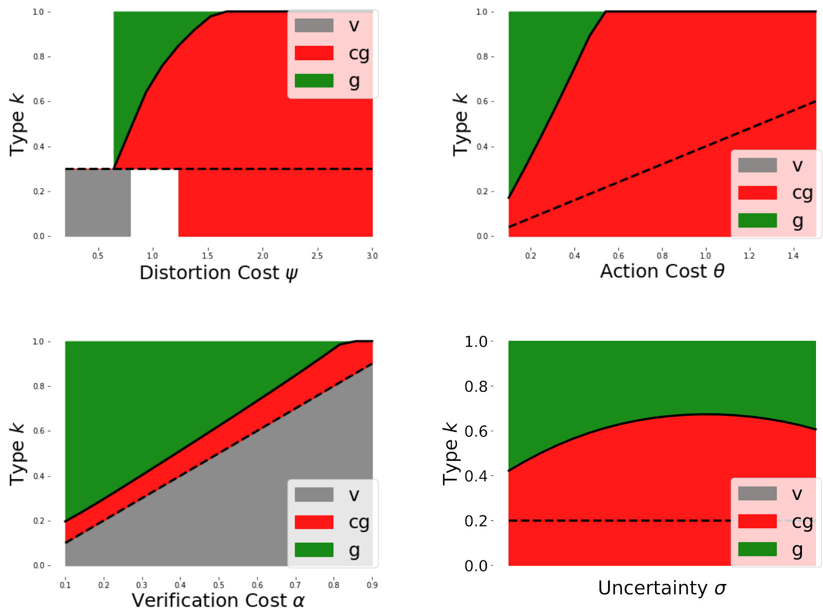
Proposition 3 states that, if it exists a (semi-) separating equilibrium, then necessarily higher types are those ones issuing the non-contingent contract g, whereas lower types are those issuing the contingent contract cg. This is because issuing a non-contingent green contract allows the good types to differentiate themselves from the group of those that would be better off keeping their types private. The existence of such equilibrium relies on the verification of the *single-crossing* property outlined in (1.30),[31] which states that the net gains from issuing the contingent contract are monotonically decreasing in the firm's type k. This happens because when the investor is poorly informed about the firm's type, the marginal effect of the type-specific distortion cost on the firm's preference for issuing a contingent contract is *diluted* by the fact that the investor averages distortion costs across the set of types that are issuing the contingent contract. On the other hand, type-specific action costs continue to play a central role in driving firm's preferences given that those costs can be correctly signalled when issuing a green bond. Proposition 3 states that in the case where $\theta < \frac{\psi}{\sigma^2}$, meaning when the action cost for the average type is sufficiently smaller relative to its distortion cost, then the role played by type-specific distortion costs becomes negligible and the marginal benefits from issuing a contingent contract decrease monotonically in the type k and are uniquely driven by their action costs (i.e. by their opportunity cost of commitment illustrated in Figure 1.2), and therefore condition (1.30) is satisfied.

Following this line of reasoning, one can also show that a semi-separating equilibrium with signalling cannot exist for types $k \in [0, 2\theta\alpha)$. Specifically, as discussed formally in the Appendix B, condition (1.30) is never satisfied when the alternative to a contingent contract is a plain vanilla contract v, because action and distortion costs cannot be disentangled and preferences for con-

[31]As outlined in Mailath [1987], the single-crossing property is necessary and sufficient for the existence of a (semi-) separating PBE in case the first mover has continuum one-dimensional types.

Figure 1.5 *Equilibrium Contract Choice - Asymmetric Information*

The plots show the firm's optimal contract choice as a function of the type k (y-axis) and the parameters ψ, θ, α, and σ respectively. Model parameters are $\theta = 0.5$, $\alpha = 0.3$, $\sigma = 1.0$ (top left plot), $\alpha = 0.5$, $\psi = 2$, $\sigma = 1.0$ (top right plot), $\theta = 0.5$, $\psi = 0.1$,$\sigma = 0.5$ (bottom left plot), and $\theta = 0.2$, $\alpha = 0.5$, $\psi = 2.5$ (bottom right plot) respectively.



tingent contracts are u-shaped as a function of firm types. As a consequence, the only possible equilibria are corner solutions in which either all firms pool at a contingent green contract, or all firms pool at a plain vanilla contract.

Importantly, by focusing on the conditional set of types that issue contingent or non-contingent green contracts in equilibrium (e.g. red and green regions in Figure 1.5), we find that non-contingent green contracts are unambiguously more likely to be issued by higher types. Specifically, Figure 1.5 shows how firm's issuance preferences vary across possible choices of the parameters ψ, θ, α and σ. Note that with asymmetric information, we obtain that across all possible choices of the model parameters that admit an equilibrium, non-contingent green debt contracts are more likely to be issued by higher types compared to contingent green debt contracts. Such prediction is markedly different from that obtained under perfect information, whereby the best types would always issue the contingent green debt, and motivates the empirical section that follows.

1.7 Empirical Testing

The analysis that follows aims to test the predictions outlined in the theoretical sections combining green securities data with issuers characteristics.

1.7.1 Data

Securities. We first compile the universe of sustainable corporate debt securities screening for Green, Social, Sustainability instrument indicators as well as for Sustainability-linked indicators in the Bloomberg's fixed income database between January 2013 through April 2021 (details are provided in the Appendix A). We find a total of 8,589 securities, of which 4,618 bonds (including Green, Social, Sustainable and Sustainability-linked), and 3,971 loans (including Green and Sustainability-linked). Consistently with earlier evidence documented in Baker et al. [2018], Table A.5 shows that sustainable bonds and loans are on average larger than ordinary bonds and loans in terms of amount issued, have a longer maturity, and lower coupon rates. Interestingly though, we find that SLBs have significantly *lower* credit ratings than Green, Social, or Sustainable bonds (Figure A.6), whereas Green loans and SLLs have similar credit ratings, although credit ratings are available only for few securities in the private sample.

We find that SLB holders are similar to Green, Social, and Sustainable bond holders (Figure A.7), and that the performance metrics on which SLBs and SLLs are written match well the observed proportions of Green, Social, and Sustainable bonds and loans in the market (Table A.6). Specifically, using information from Bloomberg New Energy Finance (BNEF) on the performance targets of SLLs and SLBs, we find that 65% of the targets are written on environmental metrics (of which about half of these environmental metrics are greenhouse gas (GHG) emissions), about 30% on social or ESG metrics, and only 5% on governance metrics respectively. These figures are in line with the overall proportion of Green, Social, and Sustainable bonds and loans in the sustainable finance market (roughly 80% of these bonds and loans are Green, whereas the remainder 20% are Social or Sustainable). This evidence mitigates concerns regarding the possibility that a firm might issue one or the other contract category depending on clientele effects, and it allows us to focus on environmental outcomes and more specifically on GHG emissions as the single most popular metric underlying green debt contacts.

Security-Issuer Data. We construct the security-issuer dataset by matching the universe of sustainable corporate debt securities from Bloomberg with issuers' financial and emissions data from Standard & Poor (S&P) Trucost.[32] The S&P Trucost database provides quality-checked carbon emissions data differentiating between Scope 1, Scope 2, and Scope 3 emissions as defined by the GHG Protocol Standard.[33] Given limitations in the availability of emissions data, we restrict our empirical analysis to the time period between 2017 and 2021, covering the years in which both contingent and non-contingent green debt categories are present in the market.[34] We also include Environmental, Social, and Governance (ESG) performance ratings in the analysis by matching firms in our dataset with the universe of firms in Sustainalytics.[35] Sustainalytics is a Morningstar rating company which measure a company's exposure to industry-specific ESG risks and how well a company is managing those risks. As reported in Appendix A, Sustainalytics is the most popular rating provider on which contingent green debt securities are written on. The final dataset comprises a total of 661 unique firms of which 476 with ESG ratings, issuing a total of 1,847 green debt securities between 2017 and 2021, where 334 of those securities are categorised as contingent green debt and the remainder as non-contingent green debt.

Table 1.1. reports summary information as of 2017 on the firms in our sample (column Issuers) comparing them with the universe of firms in Trucost (column S&P Trucost Universe). From a financial perspective, the average issuer of green debt securities is larger, has a higher proportion of debt in its capital structure, and is more profitable than the average firm in S&P Trucost. From an environmental perspective, the average issuer is more likely to self-report its emissions (and consistently with its larger size, reports higher emissions levels than the average firm in S&P Trucost), as well as more likely to be tracked by the ESG rating provider. To the extent that size and the availability of emissions/sustainable performance metrics are barriers to entry in the sustainable finance market (e.g. small firms cannot afford upfront verification costs and/or do not have the technology for writing contingent contracts), these statistics are consistent with the model prediction that issuers of plain vanilla contracts should lie at the lowest end of the

[32]We match issuers in Bloomberg with firms in S&P Trucost using their ticker symbol where possible and using the name for the remainder.

[33]The GHG Protocol Corporate Accounting and Reporting Standard provides requirements and guidance for companies and other organizations preparing a corporate-level GHG emissions inventory. Scope 1 covers direct emissions from owned or controlled sources. Scope 2 covers indirect emissions from the generation of purchased electricity, steam, heating and cooling consumed by the reporting company. Scope 3 includes all other indirect emissions that occur in a company's value chain. Source: *https://ghgprotocol.org/corporate-standard*.

[34]The year 2017 is the start of the market for sustainability-linked loans and bonds.

[35]We match the Bloomberg/S&P Trucost dataset with Sustainalytics using the company ticker symbol where possible and using the name for the remainder.

type spectrum.[36] Interestingly though, notwithstanding the green financing choice, green issuers receive only marginally better ESG ratings than the universe of ESG-tracked firms in S&P Trucost, suggesting that there is still significant variation in the environmental quality of firms.

Table 1.1. *Summary Statistics*

Data are from the Sustainalytics/Bloomberg/Trucost merged dataset. The left column (Issuers) refers to the selected sample of firms that issue at least one green debt security between 2017 and 2021, as identified from the Bloomberg's fixed income database (Appendix A). The right column (S&P Trucost Universe) is the universe of firms in S&P Trucost. Balance-sheet and emissions data are from S&P Trucost and refer to the fiscal year 2017. *All continuous variables are winsorized between the 5^{st} and the 95^{th} percentiles of the pooled distribution. $^{+}$ESG performance indicators are available for a subset of the sample.

	Issuers		S&P Trucost Universe	
Variable	**Mean**	**(Std.)**	**Mean**	**(Std.)**
Total Assets*($ bl)	10.8	(28.8)	5.14	(9.82)
Total Revenues*($ bl)	9.79	(15.8)	1.91	(3.26)
EBIT to Revenues Ratio*	0.37	(0.42)	0.14	(0.21)
Debt to Value Ratio*	0.49	(0.19)	0.31	(0.23)
Self-Disclosure of Emissions	0.68	(0.45)	0.25	(0.42)
Emissions* (ml tCO2e)	5.70	(12.7)	0.86	(1.78)
Tracked by Sustainalytics	0.65	(0.47)	0.27	(0.45)
Sustainalytics ESG Score^{+}	62.3	(11.3)	56.9	(10.4)
Unique Firms	661		14,613	

1.7.2 Issuance by Project Type

A first prediction of the model is that non-contingent green debt contracts are preferred to contingent green debt when the project's outcome has either a high level or a low level of uncertainty. In the model, an increase in the uncertainty parameter increases the component of the outcome that cannot be controlled by the firm nor credibly verified. As we interpret the green outcome in terms of GHG emissions, we aim to measure the uncertainty in GHG emissions following the guidelines of the GHG Protocol Corporate Accounting and Reporting Standard.[37] According to the protocol, the level of uncertainty in one firm's GHG emissions inventory is the combination of the uncertainty

[36] Furthermore, although not directly modelled in our framework, it should be noted that size is also increasing the expected benefits from issuance of a green debt contract, consistent with the view that large firms are more visible and likely face greater level of investor pressure as well as greater exposure to global environmental regulation.

[37] See *https://ghgprotocol.org/sites/default/files/ghg-uncertainty.pdf.*

related to the measurement of the firm's activities and the uncertainty related to the emissions factors used to convert those activities into actual GHG emissions.[38] We therefore use the GHG emissions Scope's breakdown provided by the same protocol to construct a measure of GHG emissions uncertainty.[39] Specifically, Scope 1 emissions, which are those directly produced by sources owned or controlled by the firm such as on-site fuel combustion or stationary sources, are deemed as the least uncertain by the protocol given the simple measurement of activities (delivery records and bills) and the relatively standard carbon content of each source. Scope 2^+ emissions, which include Scope 2 emissions and Scope 3 upstream emissions, capturing indirect emissions produced by the firm's suppliers and by energy usage, are deemed as having an intermediate degree of uncertainty. Finally, Scope 3 downstream emissions, which encompass all other indirect emissions produced downstream, are deemed as the most uncertain given the difficulty in the measurement of activities, which cannot be directly controlled by the firm, as well as in the choice of the emissions factors.

Making use of the Scope-level GHG emissions data from Trucost, we define an industry-level uncertainty index as

$$uncertainty_j = \frac{1}{N_j} \sum_{i=1}^{N_j} \sigma^1 w_{i,j}^1 + \sigma^2 w_{i,j}^2 + \sigma^3 w_{i,j}^3 \tag{1.31}$$

where for each firm i in industry j, the term $w_{i,j}^1$ is the proportion of Scope 1 emissions out of total emissions, $w_{i,j}^2$ is the proportion of Scope 2+ emissions out of total emissions, $w_{i,j}^3$ is the proportion of Scope 3 emissions out of total emissions, $\sigma^1 < \sigma^2 < \sigma^3$ are decreasing levels of uncertainty for each of the emissions scopes, and N_j is the number of firms in industry j.

Figure 1.6 plots the proportion of contingent debt securities relative to all green securities issued between 2017 and 2021 against the industry-level uncertainty index as of 2017. In line with the model predictions, industries with intermediate levels of uncertainty are those more likely to issue the contingent green debt. Indeed one observes that both utilities and financial firms, which lie at the end of the uncertainty spectrum having the highest share of Scope 1 and Scope 3 downstream emissions respectively, are the most popular issuers of non-contingent green debt.[40] As far as the utilities firms are concerned though, one thing worth discussing is whether environmental regulation could play an important role in shaping these firms' preferences towards green bonds,

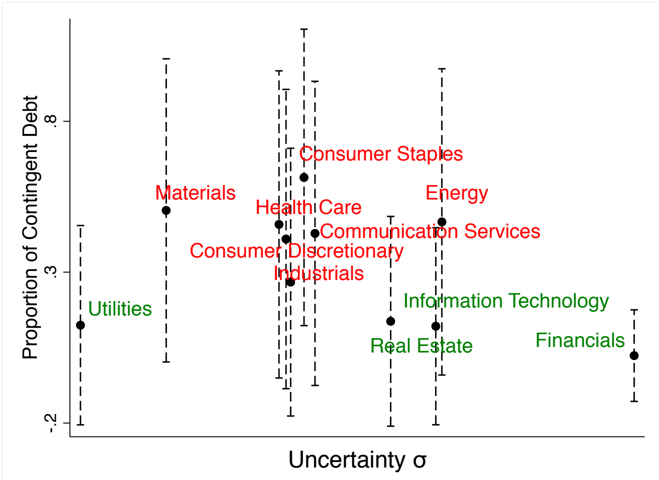
[38]There could be also direct measurement of GHG emissions through techniques that detect the concentration of GHG emissions in the atmosphere, however, this measurement method is rarely implemented by firms and therefore excluded in our analysis.

[39]See more details on the GHG Protocol website *https://ghgprotocol.org/corporate-standard.*

[40]Figure A.8 in the data Appendix A shows absolute proportions of green issuances by industry.

Figure 1.6 *Issuance Choice by Project Uncertainty*

The plot shows the proportion of outcome-contingent green debt securities out of the total green debt securities issued between 2017 and 2021 (y-axis) against industry-level uncertainty index (x-axis). The index is constructed as in (1.31) using emissions data from S&P Trucost relative to 2017. Industry sectors refer to the Global Industry Classification Standards (GICS) provided by S&P Trucost.



therefore explaining the hump-shaped pattern in figure 1.6. On the one hand, it is true that most of the green projects of utilities firms are about building low carbon infrastructures and as such, they are usually capital intensive and may be incentivized by regulators (through subsidies or other mechanisms). This would make them naturally more suitable to project-financing, and therefore to green bonds. On the other hand though, it is also true that through regulatory schemes such as the European cap and trade or the renewable energy certificates in the United States, those firms' GHG emissions and other related outcomes are already measured and verified. Therefore, compared to other industries that lack an infrastructure for measuring and reporting green outcomes, utilities should also have lower costs of issuing outcome-based contingent contracts.

1.7.3 Issuance by Firm Types

We first look for the presence of information frictions by regressing firms' green issuance choice on *observable* characteristics that should proxy for firms' environmental types. The argument is that if firms' types are correctly identified by those proxies, then we should expect a positive or insignificant correlation between contingent issuance and firms' types. On the other hand, if those proxies are only weakly correlated with firms' environmental types, then we should expect a negative correlation between contingent issuance and those noisy proxies.

In the model, good types are those that have a better ability to deliver the green outcome (i.e. a *lower* action cost) as well as a worse ability to distort the green outcome in reports (i.e. a *higher* distortion cost). Given that we focus on GHG emission as the green outcome metric, we proxy for the cost of action using the historical emissions intensity of the firm, measured as the logarithm of the firm's total emissions scopes per unit of total assets. The argument is that once controlling for location and industry effects, a higher historical emissions intensity is an endogenous outcome of higher historical abatement costs, in turn predicting lower future abatement capacity, everything else equal. Therefore, we proxy for action cost as

$$actioncost_{i,j} = log(emissions_{i,j}) - log(assets_{i,j}) \tag{1.32}$$

where for each firm i in industry j, $emissions_{i,j}$ are the sum of scope 1, scope 2+, and scope 3 emissions in kilo tons of carbon dioxide equivalent[41] (ktCO2e) and $assets_{i,j}$ refers to total assets in million dollars. Proxying distortion costs using realized manipulation is challenging in that one cannot disentangle reported from actual carbon emissions data. To circumvent this challenge, we conceptualize manipulation as *greenwashing*, defined as *selective disclosure* of information about a company's environmental or social performance so as to create an overly positive corporate image [Netto et al., 2020]. Following this definition, we measure manipulation propensity as the historical *discrepancy* between the firm's overall corporate sustainability image, as measured by the aggregate ESG score provided by Sustainalytics, and a credible signal of environmental commitment embedded in these scores, captured the firm's actual adoption of an Environmental Management System (EMS), and whether the adopted EMS is certified by a third party. In defining an EMS, the Environmental Protection Agency (EPA) explicitly ties the adoption of environmental information systems to a firms' positive environmental performance.[42] Furthermore, Lyon and Maxwell [2011] provide evidence that corporate adoption of a high-quality EMS reduces incentives for greenwash, in that a well functioning EMS not only increases the firm's information about the green outcome but it also makes it more difficult for the firm to manipulate the measurement system

[41] Carbon dioxide equivalent or CO2e is a term for describing different greenhouse gases in a common unit. For any quantity and type of greenhouse gas, CO2e signifies the amount of CO2 which would have the equivalent global warming impact.

[42] Specifically, the Environmental Protection Agency (EPA) defines an environmental management system (EMS) as *[..] a framework that helps an organization achieve its environmental goals through consistent review, evaluation, and improvement of its environmental performance. The assumption is that this consistent review and evaluation will identify opportunities for improving and implementing the environmental performance of the organization.* See *https://www.epa.gov/ems/learn−about−environmental−management−systemswhat−is−an−EMS*. The most widely used EMS standard is the International Organization for Standardization (ISO) 14001 developed by the Environmental Protection Agency (EPA) and the Eco-Management and Audit Scheme (EMAS) developed by the European Commission.

which monitors those outcomes. Therefore, we proxy for distortion cost as

$$distortioncost_{i,j} = ems_{i,j} - esg_{i,j} \tag{1.33}$$

where $esg_{i,j}$ is the industry-standardized ESG score of firm i in industry j and $ems_{i,j}$ is the sub-component of the score that indicates whether the firm has adopted an EMS and whether the EMS has been externally certified. The assumption in our model that the costs of action and distortion are negatively correlated is supported by empirical evidence reported in Table A.7 in Appendix A which confirms a negative correlation between the selected proxies for actions and distortion costs also controlling for industry and location fixed effects.[43]

Table 1.2. reports linear regressions of firm's issuance choice on the selected proxies for firm types. The dependent variable is a dummy equal to 1 if the firm issues only non-contingent debt securities between 2017 and 2021. The regressors are the firm's action and distortion costs proxies as well as other controls for the firm's financial conditions, all as observed in 2017. The column Regression I refers to the entire sample of firms, while column Regression II refers to the subsample of firms tracked by Sustainalytics. The first thing to note is that the cost of action, as proxied by the firm's historical emissions intensity, is strongly positively correlated with the propensity to issue a contingent green debt contract. Importantly, the correlation remains statistically significant across both the sample choices and when controlling for industry fixed effects, financial characteristics, as well as for location fixed effects. One notes that firms issuing contingent securities have lower revenues relative to non-contingent green debt issuers in the same sector, which interpreted in light of the recent evidence in De Haas, Martin, Muûls, and Schweiger [2021] that financial constraints inhibit corporate investment in green technologies, provides further support to the model prediction that contingent debt issuers are not the best environmental types. Interestingly, contingent issuers are more likely to self-disclose emissions voluntarily than the remainder of green issuers in the same sector, but the significance seems to be mostly driven by location fixed effects.[44] On

[43] The regression Table shows that the correlation flips sign and becomes statistically insignificant when controlling for firm's financial characteristics. The reason is primarily related to the fact that firm's revenues, which are strongly negatively correlated with action costs, are also strongly positively correlated with the firm's overall ESG score (without any effect on the EMS-related sub-component of the score), therefore capturing other the relation between action and distortion costs.

[44] It is worth noting that in the empirical literature on corporate environmental disclosure, there are sharply conflicting results regarding the relationship between the firm environmental performance and its disclosure propensity. For example, Cho and Patten [2007] find that firms with worse environmental records have higher levels of environmental disclosures, while Clarkson, Li, Richardson, and Vasvari [2008] find that firms with better environmental records have higher level of disclosure. In their theoretical study, Lyon and Maxwell [2011] argue that one should expect a non-monotonic relationship between expected environmental performance and disclosure propensity.

Table 1.2. *Security Choice - Linear Regressions*

Linear regressions of green debt security choice between 2017 and 2021 on issuers characteristics as of 2017. The dependent variable is a dummy indicator equal to 1 if the firm issues uniquely an outcome-based contingent green debt contract in the observation period, and 0 otherwise. Regressors are collected from Bloomberg/Sustainalytics/S&P Trucost merged dataset. *,**,*** indicate statistical significance at the 10%, 5% and 1% level respectively.

Regressor	Regression I			Regression II		
Cost of Action	0.06***	0.04**	0.05***	0.07***	0.04**	0.04**
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Cost of Distortion				-0.01***	-0.01***	-0.01**
				(0.00)	(0.00)	(0.00)
Log Revenues		-0.03**	-0.02		-0.06***	-0.03*
		(0.01)	(0.01)		(0.02)	(0.02)
EBIT to Revenues Ratio		0.07	0.04		0.03	-0.01
		(0.05)	(0.05)		(0.07)	(0.07)
Debt to Value Ratio		-0.16	-0.14		-0.13	-0.09
		(0.10)	(0.09)		(0.12)	(0.12)
Self-Disclosure of Emissions		0.16***	0.03		0.01	0.02
		(0.04)	(0.04)		(0.01)	(0.05)
Tracked by Sustainalytics		0.01	0.02			
		(0.04)	(0.04)			
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	No	Yes	Yes	No	Yes	Yes
Location Dummy	No	No	Yes	No	No	Yes
$\mathcal{R}^2$	0.11	0.18	0.26	0.14	0.21	0.28
Unique Firms	647	647	647	476	476	476

the other hand, as summarized by the regression coefficients on the dummy variable Tracked by Sustainalytics, it seems that being publicly rated at the sustainability level is not a statistically significant determinant of the firm's issuance choice, consistently with the fact that conditional on the issuance of green debt, issuance choices are not driven by a different cost of access to the technology on which contingent securities are written on. Moving on to the subsample of firms tracked by Sustainalytics, one finally notes that issuers of contingent debt contracts also have significantly lower distortion costs relative to the remainder of green issuers in our dataset, as proxied by our metrics of greenwashing, an effect that remains statistically significant when controlling for industry fixed effects, financial characteristics, as well as for location fixed effects.

1.7.4 Ex-post Debt Performance

To complete the analysis, we look at the ex-post financial performance of contingent and non-contingent green debt securities. We recall that in the model, because of a binding investor participation constraint in equilibrium, all securities issued are expected to yield zero total returns. Specifically, the interest rate on each green debt contract is set to offset – in expectation or across states – the green outcome delivered by the project, in such a way that the monetary and green returns sum to zero. As a consequence, the model predicts that in presence of asymmetric information, contingent green debt contracts issued by lower firm types are expected to yield higher monetary returns so as to compensate the investor for lower green outcomes. To test this implication, we look at differences in the *green bond premia* across the two types of green debt securities, namely contingent and non-contingent debt, where the green bond premium is defined as the negative yield differential between green bonds and the conventional bond counterparts traded in the secondary market. Our empirical estimation follows the methodology in Zerbib [2017], but we are interested in yield differentials across contingent and non-contingent green debt rather than estimating the magnitude of the green bond premium per se.

For this analysis we restrict our attention to the sample of public debt and disregard private green debt securities, namely green loans and sustainability-linked loans. Specifically, we estimate the green premium of green, social, and sustainable bonds (non-contingent green bonds) and compare it with that one of sustainability-linked bonds (contingent green bonds) by using a matching methodology which consists of constructing pairs of securities with the same properties except for the one property whose effects we are interested in. That is, for each green issuer summarized in Table 1.1., we first collect from Bloomberg the list of conventional bonds issued by that same firm in the same year, finding a total 5,059 of conventional bond issuances against 754 total green issuances (79 contingent and 675 non-contingent bonds respectively). We pair each of the 754 green securities with a conventional bond (or a set of conventional bonds) with similar characteristics from the same issuer, meaning one with the closest maturity, bond type, coupon type, issue year and currency. We disregard differences at the rating level given that only half of the securities are rated. However, in green premium determinants regressions we account for differences in credit ratings at the issuer-level, as well as maturity and coupon biases due to the fact that maturities and coupon rates are not exactly equal. This exercise leaves us with a dataset of 368 pairs of green-conventional bonds (of which 29 contingent green-conventional and 339 non-contingent green-conventional respectively). For each pair of green-conventional bonds, we collect weekly ask yields since the issuance of the green security until the second week of September 2021, and measure the green premium as the average yield differential between each pair of green and conventional bonds.[45] We use average differentials in bid-ask spreads across green and conventional bonds to control for yield differences related to the liquidity bias (see Beber, Brandt, and Kavajecz [2009]).

Table 1.3. *Debt Performance - Linear Regressions*

Linear regressions of the green bond premium on the bonds characteristics. The premium is expressed in average percentage differences in ask yields between green bonds and their conventional bond counterparts. The variable Issue Amount is the amount of green bond issuance in $ billions. The variables ΔLiquidity, ΔMaturity, and ΔCoupon refer to differences in average bid-ask spreads, maturity, and coupon rates across the pairs of securities. All variables are collected from Bloomberg. *,**,*** indicate statistical significance at the 10%, 5% and 1% level respectively.

Regressor	Green Premium		
Constant	-0.35	-0.28	-0.30
	(0.94)	(0.60)	(0.62)
Contingent Debt	0.06	0.08	0.30*
	(0.17)	(0.15)	(0.18)
log(Issue Amount)		-0.01	-0.01
		(0.03)	(0.03)
ΔLiquidity		-0.76**	-0.49*
		(0.32)	(0.30)
ΔMaturity		0.06***	0.06***
		(0.01)	(0.01)
ΔCoupon		0.03	0.03
		(0.03)	(0.02)
Currency Dummy	Yes	Yes	Yes
Bond Type Dummy	Yes	No	Yes
Coupon Type Dummy	Yes	No	Yes
Issuer Rating Dummy	No	No	Yes
$\mathcal{R}^2$	0.61	0.70	0.72
Unique Matches	368	368	368

Table 1.3. shows the results of the regression of the green premia for each green-conventional bond pair against a selected set of bonds characteristics. The first column shows that when controlling for currency, bond structure, coupon type and issue year, we find negative yet statistically insignificant green premia of approx -35 basis points between non-contingent green and conventional bonds, and approx -29 basis points between contingent green and conventional bonds. In other words, the green bond premium seems to be 6bp larger for non-contingent green bonds than

[45] We select ask yields following the methodology in Zerbib [2017]. When more than one conventional bond is available, we take the average across each of the ask yields. If, on a specific week, the green or conventional ask yields are not available, we remove that observation from the dataset. The result is a cross-section of 368 green premia.

contingent green bonds, consistent with the evidence summarized in Table 1.2. which indicates that bad types are more likely to issue contingent green debt, although regression coefficients are not statistically significant. Column two shows that the results do not change when accounting for liquidity effects, residual differences in maturity and coupon rates, as well as differences in amount issued, although the magnitude of the coefficients changes as liquidity and maturity seem to be relevant determinants of yield differentials. Interestingly, the third regression shows that when controlling for rating differences at the issuer level, the positive difference across contingent and non-contingent yield spreads becomes larger (30bp on average) and statistically significant (see also Figure A.10 in the Appendix A). This is in line with evidence that issuer credit rating is one of the strongest determinants of cross-sectional variation in green bond premia reported by Zerbib [2017] and more recently by Larcker and Watts [2020]. Taken together, the reduced-form evidence reported in Table 1.2. and Table 1.3. supports the presence of information frictions causing adverse selection in the sustainable finance market, implying that financial markets are not yet channelling funds efficiently to sustain the transition to a green economy.

1.8 Concluding Remarks

This paper takes account of recent market developments, and develops the first theoretical model that formally captures the key features of the two types of debt contracts on the growing market for sustainable finance. The most prevalent type of green debt contract in the sustainable finance market is the green bond, a fixed income debt instrument which earmarks proceeds for specific green projects, but makes no commitment to deliver green outcomes. In contrast, the newly emerging class of sustainability-linked bonds and loans does not impose ex-ante constraints on the use of proceeds, but instead embeds contingencies that ensure commitment to outcomes. These contingent green debt securities should address the limitations inherent in the design of green bonds by eliminating the need to restrict borrower's actions ex-ante and by making outcomes rather than intentions the focus of green projects financing, yet the observed market outcome points to the co-existence of project-based non-contingent contracts and outcome-based contingent contracts, with some firms employing both. We develop a model of firm financing which incorporates an investor with green preferences into an otherwise standard framework of corporate financing with asymmetric information. Firms seek to finance green projects whose outcome embeds an uncertain, non-measurable component that is revealed only to the firm and can be manipulated. We demonstrate that the co-existence of the two green debt contracts is an equilibrium result when green outcomes are manipulable and firm types differ in their ability to manipulate. In presence of asymmetric information about firms' type, green bonds can be used as an expensive screening device, and we find empirically that contingent green debt securities have lower green premium and are issued by more emissions intensive firms.

Chapter 2

Beliefs about Climate Regulation and Emissions Abatement[1]

2.1 Introduction

Climate change poses a looming threat to economic and financial stability, even as we deal with current events, lending urgency to calls for action on global warming.[2] Faced with such warnings, in December 2015, 196 nations signed an agreement at the United Nations Framework Convention on Climate Change (UNFCCC) in Paris, to limit greenhouse gas emissions to a level consistent with global temperatures rising less than 2°C. The agreement also determined a five-year window within which countries could meet and renew the so-called Nationally Determined Contributions (NDCs). However, most signatory countries are falling far short of required targets,[3] and the world's second largest emitting country has withdrawn from the agreement.[4]

How important is such coordinated climate regulation in determining firms' carbon mitigation, and through what channels does such regulation affect firms? In this study, we pursue a bottom-up approach to these questions. We analyze comprehensive micro data from firms' voluntary disclosures about their beliefs about regulation, and their plans for and current actions on abatement. In the years leading up to and following the Paris announcement, we uncover significant

[1]This chapter is joint work with Tarun Ramadorai, and adapted from the working paper *Climate Regulation and Emissions Abatement: Theory and Evidence from Firms' Disclosures*, 2019.

[2]For example, see Carney [2015].

[3]Information on the Nationally Determined Contributions (NDCs) can be found at *https://unfccc.int/process/the-paris-agreement/nationally-determined-contributions/ndc-registry*.

[4] In June 2017, U.S. President Donald Trump announced his intention to withdraw from the agreement, with the final decision made in November 2020.

and striking variation in these variables. We then build a set of dynamic models of emissions abatement to better understand which combination of model ingredients can best rationalize the patterns observed in the data. We match the model-implied dynamics of firms' emissions abatement choices to the data up to and just following the Paris announcement, recovering estimates of key parameters such as the adjustment costs associated with abatement, and the extent to which firms respond to one anothers' actions.

Our analysis reveals that firms' reported beliefs about climate regulation events strongly influence their planned and actual abatement activities. Moreover, cross-firm reputational externalities, and cross-firm information asymmetry about the stringency of the regulatory policy are two important model ingredients needed to match the patterns and magnitudes seen in the data. These ingredients amplify firms' reactions to climate regulatory announcements, leading us to conclude that climate regulation can have substantial effects on firms' abatement actions. Finally, we validate these estimated parameters as well as the model in an out-of-sample exercise, in which we predict abatement actions from firms' revised beliefs following U.S. President Trump's announcement to pull back from the Paris agreement.

Our data tracks North American public firms that voluntarily disclose environmental information through the Carbon Disclosure Project (CDP) between 2011 and 2017. We verify the accuracy of these data using third-party sources (such as Bloomberg, Thomson Reuters, and MSCI) who produce external audits and ratings of firms' ESG activities. The CDP data comprise three important dimensions, namely, firms' self-reported beliefs about the horizon and impact of future climate regulation; firms' plans for future carbon emissions abatement; and finally, data on firms' emissions abatement actions to date, which reflect the actual changes in their carbon footprints. In our empirical work, we compare, at each reporting date, the dynamics of firms' reported beliefs about the intensity of future climate regulation with their carbon abatement actions. We document that there are important cross-sectional differences between two groups of firms in the data. One set comprises firms that publicly report their plans for future emissions reduction in addition to reporting their beliefs about the intensity of future climate regulation, as well as their current actions on abatement. The other set comprises firms that report beliefs and current abatement actions, but do not report their plans for future abatement. The two sets of firms differ in several other ways. The plan-reporting firms are larger and more profitable, more emissions intensive, and also have a greater propensity than non-plan-reporting firms to a) engage with policymakers, and

b) provide direct funding to climate regulatory activities.

Between 2011 and 2015, prior to the Paris announcement, both plan and non-plan reporting firms, on average, steadily downgraded their expectations over the impact of future regulation, and progressively increased their actual carbon footprint. However, this tendency is more muted for the firms that consistently report plans for future emissions reduction—their reported beliefs about future climate regulation change more slowly, and they exhibit more consistent emissions reduction over this pre-Paris-announcement period. These patterns change following 2016, the first reporting year following the December 2015 Paris announcement. In 2016, all firms report modestly upwardly revised beliefs over the impact of climate regulation, and all firms sharply increase carbon abatement over the year from 2016 to 2017.[5] There is interesting heterogeneity in these responses. While both plan and non-plan reporting firms upwardly revise their beliefs about future regulation intensity, the belief revisions of plan-reporting firms are considerably *smaller* than those of non-plan reporting firms. Despite this fact, plan-reporting firms react *far more* to the Paris announcement than non-plan-reporting firms. Put differently, plan-reporting firms have *more* extreme reactions to the climate regulation event, despite being seemingly *less* surprised by the announcement of the agreement.[6] These three observations: a) that revisions in beliefs are far less pronounced than revisions in actions; b) that there is considerable heterogeneity in responses to the Paris announcement, and c) that reported beliefs don't map similarly across groups of firms to their observed actions after the announcement are important targets for any model, and together suggest that subtle economic forces are at play.

To better understand and rationalize these patterns, we begin by building a simple dynamic model of a representative firm's emissions reduction activities. In the model, the polluting firm produces output in each period using capital stock in place, with carbon emissions assumed proportional to produced output. The firm is exposed to a future climate regulation event, which we assume takes the form of a terminal carbon levy. At any time period prior to the regulation event, the firm can abate or increase emissions by reducing or increasing its level of polluting capital, but it faces standard convex adjustment costs for taking these actions. The firm's optimal policy balances the tradeoff between output growth and emissions reduction. Since the carbon levy only makes its

[5] This evidence adds to a recent work by Tenreyro and De Silva [2021] on the effect of international climate agreements on greenhouse gas emissions and other economic outcomes.

[6] Indeed, the reported plans of these firms in the year *prior* to the Paris announcement forecast their actual emissions reduction rates even *after* the Paris announcement, intensifying the puzzle about their more extreme reactions to the announcement.

appearance at the terminal date, the firm discounts the cost of regulation to the present, and sets an optimal abatement profile (plan) beginning in the current period—i.e., its current abatement action—and then for every period leading up to the date of the levy.

We take this simple model to the cross-sectional average of plan-reporting firms' reported disclosure data, feeding the model with the average of reported beliefs about future climate regulation to generate predicted plans and actions at each date, allowing the model to calibrate the expected terminal levy, the productivity of polluting capital, and emissions adjustment costs. We set the date of the imposition of the carbon levy to 2020, the first ratification deadline of the Paris agreement, which is also the most frequent deadline for planned emissions reduction reported by the firms in the data. We find that the resulting dynamics of abatement actions implied by this simple model are excessively smooth, and fail to capture the substantial increases in abatement seen in the data around the Paris announcement.

To improve the performance of the model, we therefore introduce a second firm into the economy, to capture the observed heterogeneity between plan- and non-plan-reporting firms. In addition to capturing the differences observed in the data, we seek to understand whether there are strategic interactions between these two groups of firms (those that do and do not report plans for future emissions reduction) that can simultaneously rationalize the small observed belief revisions and the large aggregate responses to the Paris announcement. We therefore add two ingredients to the model.

First, we add a reputational externality which connects each firm's profits to the abatement actions of the other firm. The specific parameter that we add controls the extent to which each firm's profits from having higher levels of polluting capital are reduced (the parameter is positive), or alternatively increased (negative), to the extent that the other firm abates emissions at the same time. When we calibrate this parameter to the data, we find that it is strongly positive, providing evidence of relative performance evaluation of firms along the dimension of their Environmental, Social, and Governance (ESG) activities.[7]. This feature of the model amplifies the impact of firms' beliefs about climate regulation on their physical actions on abatement in the model, helping to match the evidence in the data around the Paris announcement.

[7] We use news sources to document a spike in attention to ESG coinciding with the Paris announcement

The second ingredient that we add to the model is an information asymmetry across firms. We assume that the true intensity of the carbon levy is the sum of a (constant) public component that is visible to both firms, and a signal which is only visible to a subset of firms, which we map in the data to plan-reporting firms. This is motivated by evidence of heterogeneity across plan- and non-plan-reporting firms along a set of dimensions which are likely to impact firms' information quality. For one, we show corroborating evidence from CDP that plan-reporting firms engage more with climate regulators, and are more likely to provide direct funding to climate regulatory activities. Moreover, to the extent that paying attention to and processing information about climate regulation is a costly and time-consuming activity, we note that plan-reporting-firms are larger and more emission intensive, bolstering their stronger incentives to acquire, and ability to benefit from such information.

Adopting these two assumptions, we solve, in the enriched model, for the equilibrium of a dynamic Stackelberg leadership game where the more informed firm (the leader) has a first-mover advantage over the less-informed firm (the follower). The leader maximizes profits, internalizing the follower's reaction to its actions, which rationalizes the fact that plan-reporting firms respond more aggressively to the Paris announcement in the data, despite being less surprised by the announcement. We take this more complex model to the data, allowing for the size of the parameter governing the reputational externality to be structurally estimated.

Our first finding from this model is that firms' actions are consistent with an expected prior about the carbon levy of roughly 85\$/mt CO_2e. This estimate falls in the range estimated by the extensive literature on the social cost of carbon (see, e.g., Tol [2011]), and is far higher than the current implied market levy. For example, the price of carbon allowances currently traded in the European cap and trade market average around 30\$/mtCO_2e; and between 2010 and 2017, the US government's official estimate of the social cost of carbon, as provided by the inter-agency working group (IWG), averaged around 52\$/mtCO_2e.[8]

The more richly parametrized model, as we might expect, yields predictions that are closer to the observed data—although it is worth pointing out that this is not just mechanical, since the model now needs to fit the average disclosures of *both* plan-reporting and non-plan reporting firms.

[8] In 2017, the Trump administration disbanded the IWG, using since that time estimates of the social cost of carbon that range between 1\$ and 7\$/mtCO_2e.

Moreover, the model delivers several other useful predictions. First, as expected, the reputational externality generates an amplified reaction by firms to changes in the levy, with the leader (i.e., plan-reporting, in the data) firm reacting more than the follower (non-plan-reporting) firm because of its leadership position in equilibrium. Second, as the follower has no knowledge of the leader's private signal of the levy, the leader's reaction to the public component of the levy is greater. Finally, if we assume that reputational externalities are highest in the short-run and decline over time, a belief that the carbon levy will be sufficiently high can generate a declining time-path of abatement, i.e., the model predicts that firms will optimally abate a large share of their polluting capital immediately. Put together, these predictions generated from the extended model help to better fit the observed dynamics of firms' abatement plans and actions before and after the announcement of the Paris agreement. They help to explain why the reactions to the Paris announcement are both high—the new model ingredients result in substantial amplification of the short-term impacts of climate regulation relative to the basic model—and different across the two groups of firms. The amplification increases in the size of the carbon levy, and is in line with the discussion in Bénabou and Tirole [2010] about the fact that standard Pigouvian tax levels might well be amended to account for pro-sociality.

We evaluate the optimal path of carbon emissions generated by the calibrated models for a time horizon of ten years and two policy scenarios corresponding, respectively, to distributed levies (i.e., applied at each time period) of 85\$/mtCO_2e and 125\$/mtCO_2e. According to recent academic studies (see Carleton and Greenstone [2021]), a social cost of carbon updated to respond to the frontier of climate science would average around 125\$/mtCO_2e.) Comparing these cases, the augmented model predicts, in the more stringent case, an even more substantial amplification of the firm's baseline reaction to the policy in the short run.

In a final exercise, to validate these estimated parameters as well as our conclusions from the model, we acquire data to extend our sample through 2019, to evaluate the impacts of Trump's announcement in June 2017 to pull back from the Paris agreement. We show that firms' reported beliefs about the intensity of future climate regulation following Trump's announcement drop sharply, with larger reported belief updates seen for plan-reporting firms. At the same time, we see that firms report revisions to their expected horizons of emissions abatement, which are pushed further into the future. We feed these reported beliefs from the extended sample into the model with parameters fixed at their estimated values in the pre-2017 period, and demonstrate that the complex model that we estimate is well able to capture the patterns seen in emissions abatement in the out-of-sample period. This helps to provide confidence in our parameter estimates and the more complex model with cross-firm interactions that we develop.

The remainder of this chapter is structured as follows: in the rest of this section, we discuss some of the academic literature that is related to our work, and highlight our contributions to this literature. Section 2.3 introduces the CDP dataset, validates the disclosure data using external sources, and describes the construction and measurement of the empirical evidence. In Section 2.4, we describe and solve the simple dynamic abatement model with an atomistic firm, and calibrate it to the data. Section 2.5 introduces, solves, and calibrates the more complex two-firm model, and discusses the differences between this model and the simple model. Section 2.6 describes our out-of-sample exercise, and Section 2.7 concludes. An online appendix contains more detailed descriptions of the underlying data and our constructed measures, detailed model derivations, and auxiliary exercises.

2.2 Related Literature

Our work fits into the fast-growing literature on climate economics and finance that studies the interplay between corporate environmental regulation and firm behavior. Our finding that firm priors about the carbon levy appear to be far higher than the current market-implied levy supports work in Barnett, Brock, and Hansen [2020] that quantifies the negative impact of climate-related uncertainty. Our estimate suggests that the resolution of uncertainty associated with a climate policy announcement leads to firms internalizing a carbon levy far higher than the one observed in the market. Given that carbon prices will need to be raised substantially to meet the 2°C target established at the Paris agreement (see, e.g. Nordhaus [2018]), to the extent that our estimates of firms' implied priors are credible, they constitute evidence that a large rise in the carbon levy might not come as a shock to firms.

An important strand of this literature focuses on the effects of imperfect regulation on firms' investment and production choices. For example, Fowlie [2009], Martin, Muûls, De Preux, and Wagner [2014b], and more recently Bartram, Hou, and Kim [2019] show theoretically and empirically how imperfect competition, information asymmetry and financial constraints respectively interact with an incomplete regulatory framework to alter firms' response to policy changes. Relatedly, Aghion, Dechezleprêtre, Hemous, Martin, and Van Reenen [2016] use evidence from the auto industry and a model to show that informational frictions significantly influence the clean innovation path of regulated firms, while Pindyck [2007] and Pindyck [2013] quantify the delay induced by policy uncertainty on firms' optimal abatement timing. Externalities studied in these papers generally result in policy outcomes that are worse than those in the baseline frictionless, competitive scenario. In contrast with these studies, the reputational and informational externalities that we study make regulatory policy *more* effective. Moreover, some firms can benefit in our setting, meaning that in addition to a risk requiring firm hedging, regulatory events are also a potential opportunity for some firms.[9]

The reputational externality in our model connects our work to the empirical and theoretical literature on the effect of herding and information externalities on firms' investment choices (see, for example, Chamley and Gale [1994], Leary and Roberts [2014] and Décaire, Gilje, and Taillard [2019]). Grenadier [1999] investigates the role of information externalities in combination with payoff externalities, and Grenadier, Malenko, and Strebulaev [2014] focuses on the specific interaction of information and reputation externalities. To our knowledge, our model is the first one to assess this interaction in the context of emissions reduction, and our empirical work provides evidence of its importance.

We find that firms are highly responsive to signals of future regulation; in line with our findings, previous literature including Engau and Hoffmann [2009] and Bui and De Villiers [2017] shows that firms update their climate management strategies in response to changes in environmental policy risk. In related work, Zingales and Shapira [2017] and Barrage, Chyn, and Hastings [2020] outline that large public firms act strategically and internalize the costs of pollution even in the absence of specific regulations. Relatedly, Shive and Forster [2019] investigates the impact of corporate governance externalities on firms' environmental behavior, finding that publicly listed firms tend to pollute more. The paper attributes this finding to listed firms facing increased pressure from short-term investors.

There is also extensive empirical work on the determinants of corporate engagement in sustainability practices. Several papers show evidence that aligns with our findings in this study. Among

[9]Prior literature has also investigated the profitability of climate regulation in the context of market-based environmental policies (see, for example, Bushnell, Chong, and Mansur [2013]).

others, Artiach, Lee, Nelson, and Walker [2010], Martin, Muûls, de Preux, and Wagner [2012], and Luo, Lan, and Tang [2012] document a positive association between climate engagement and firm productivity, while Ovtchinnikov, Reza, and Wu [2019], Zhang, Ye, Yang, and Zhou [2019], and Heitz, Wang, and Wang [2019] point out that political connections and proximity to policymakers also help to explain corporate engagement in environmental activities.

Finally, our work also relates to the fast-growing literature on corporate sustainability ratings, ESG, and firm value. Drawing from information collected from the CDP dataset, Matsumura, Prakash, and Vera-Munoz [2014] show that higher ESG disclosure scores are associated with higher firm value. Engle, Giglio, Lee, Kelly, and Stroebel [2019] show that hedging strategies against negative climate-change news that rely on the use of ESG ratings data outperform alternative approaches, while Bolton and Kacperczyk [2019] show that firms with higher total CO2 emissions earn higher returns. Recent work such as Dyck, Lins, Roth, and Wagner [2018], Hoepner, Oikonomou, Sautner, Starks, and Zhou [2018], and Krueger, Sautner, and Starks [2020] shows that institutional investors are highly concerned with firms' exposure to climate risks, and engage actively with them in the management of ESG practices, while Hong and Kacperczyk [2009] show that "sinning" firms are shunned by such investors. Relatedly, Hartzmark and Sussman [2019] studies announcements of mutual funds' sustainability ratings, and argues that investors reacted by reallocating capital to funds in a manner that reveals their preferences for sustainability—providing evidence for the existence of a reputational externality in a different setting to ours.

2.3 Data

2.3.1 Carbon Disclosure Project (CDP) Data

We employ detailed data on firms' voluntary disclosures from the Carbon Disclosure Project (CDP) (https://www.cdp.net/en), an international, not-for-profit organization providing a system for companies to measure, disclose, manage, and report environmental information. CDP sends out detailed questionnaires to a large set of firms each year, and we obtain the annual responses to these questionnaires from 2011 to 2017. These data provide information rarely available in SEC-mandated 10-K annual reports, and information that is only occasionally provided by voluntary firm CSR reports.

In this study, we focus our attention on three particular sets of firm disclosures in these questionnaires, namely, (i) firms' self-reported measures of their current carbon emissions (henceforth referred to as their *actions*), (ii) firms' forecasts of the future impact of environmental regulation on their operations (henceforth referred to as their *beliefs*), and (iii) firms' self-reported targets for future emissions reductions (henceforth referred to as their *plans*). We describe how we convert the raw data from CDP into the specific measures that we use in our empirical analysis later in this section, but first describe the construction of our sample below.

While it does provide detailed information on firms' environmental activity, we should mention here that the CDP dataset does have several major limitations. First, firms self-report to CDP, meaning that the data comprise a selected subsample of the CRSP COMPUSTAT universe (see, for example, Luo et al. [2012]). More specifically, firms in the dataset are substantially larger than the average firm in the universe. While this does introduce concerns about external validity, it is worth noting that these firms comprise a substantial fraction (25%) of the total emissions reported in the US. Second, since the information reported in CDP is voluntary and not subject to third party auditing, it is potentially subject to "greenwashing".[10] We are therefore careful to assess the validity of the disclosures in CDP on firms' carbon footprint, their beliefs about the expected impact of regulation, and their reported plans for future abatement using a range of internal and external data. This includes three different datasets (Bloomberg, Thomson Reuters, and MSCI) of third-party verified indicators of firms' sustainability collected from publicly available sources.

2.3.2 Sample Construction

To construct our dataset, we match the CDP data to the CRSP COMPUSTAT North America merged database, which is a panel of 6,051 public firms reporting data over the 2010–2016 accounting period.[11] To ensure that we can measure firms' changing actions and revisions of their beliefs about regulatory risks, we require that firms in CDP report *both* current carbon emissions and their forecasts of the future impacts of regulation for at least two consecutive years in the dataset. Firms also have the option of self-reporting their targets for future emissions reductions (i.e., their plans), resulting in firms that reported as well as those that did not report plans in the *previous year*, a distinction that we return to during our analysis of the data. When we match the

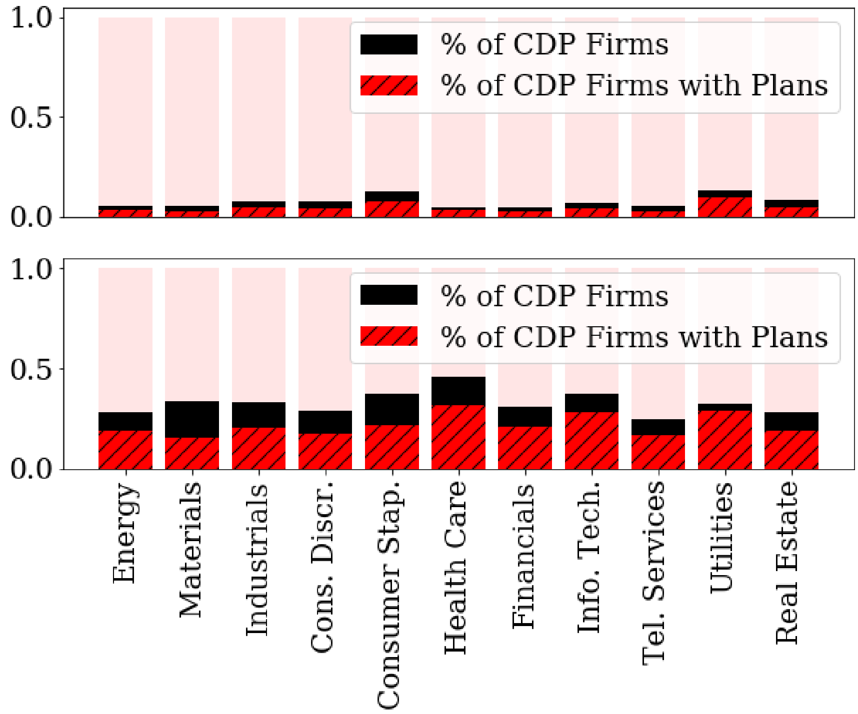
[10] Greenwashing is the use of marketing to portray an organization's products, activities or policies as environmentally friendly when they are not.

[11] We keep only firms in the CRSP/COMPUSTAT North America (Fundamental Annual) dataset with non-missing Tickers and Total Assets within the 2010–2016 accounting period. We lag the information from CRSP/COMPUSTAT by one year to account for a time window between the filling and the final release of the CDP questionnaires.

CDP data to the CRSP COMPUSTAT sample after applying these filters, the sample comprises a total of 449 unique North American public firms, with between 227 and 368 firms reporting in any given year between 2011 and 2017.

Figure 2.1 *Sector Composition and Market Capitalization*

Summary statistics of the CRSP/COMPUSTAT North America universe and the CDP subsample, as of 2017. The top histogram summarizes the proportion of CDP firms in the CRSP/COMPUSTAT North America universe at the GICS two digit level, the bottom histogram summarizes the proportion of total market value (MKVALT from CRSP/COMPUSTAT as of 2016) represented by these firms. Black (red) bars refer to the total of CDP firms (subset of CDP firms that disclose plans for at least one previous reporting period) in our sample.



The top panel of Figure 2.1 shows, in the last reporting year 2017 in our data, the fraction of firms in the CRSP COMPUSTAT North America universe that are in our final merged sample of firms. Each bar represents a broad GICS industry. The fractions of firms reporting and not reporting future emissions reductions plans are represented in red and black respectively. Relative to the CRSP COMPUSTAT universe, there are more firms in the merged sample in Consumer Staples, Materials, and Utilities, and fewer Financial and Health Care firms, though these differences are not substantial. Firms that report plans for future emissions reduction are overrepresented in Utilities, though this is the exception rather than the rule—a roughly similar number of firms report and do not report plans in each industry.

The bottom panel of the figure shows that despite the number of firms in the left panel comprising less than 15% of the total *number* of firms, the firms in the merged sample account for 20% to 50% of the total *market capitalization* across all industries, meaning that firms that report to CDP are substantially larger than the average firm in the universe. It is also worth noting here that in 2017, the sample firms emit a total of 1,722 million metric tonnes CO_2e, which represents roughly 25% of the total emissions produced in the United States in 2017.[12] Table 2.1. shows

Table 2.1. *Financial and Sustainability Indicators: Summary Statistics*

Summary statistics (mean and 95^{th} percentile) of the CRSP/COMPUSTAT North America universe compared with the CDP subsample over the 2010–2016 accounting period. The column Plan (No Plan) refers to the subset of CDP firms that disclose plans for at least one previous reporting period (never disclose plans). Market Value (MKVALT), Total Assets (AT), Total Liabilities (LT) and Income Before Extraordinary Items (IB) are provided by CRSP/COMPUSTAT. Return on Operating Assets (ROA) is computed as Income/(Total Assets - Total Liabilities), expressed in percentage terms. Weighted Average Cost of Capital (WACC) and Altman Z-Score are built-in functions provided by Bloomberg Equities. Environmental, Social and Governance (ESG) disclosure scores are provided by Bloomberg ESG Data Service (1), Asset 4 ESG (2), and MSCI (3) respectively. Emissions are collected from CDP disclosures (as detailed later in the section and in the appendix C). Emissions intensity is computed as Emissions/Total Assets, expressed in $\frac{\text{mtCO}_2\text{e ml}}{\text{\$ bn}}$. All variables are collected at the annual level.*,** indicates that the variable has been winsorized between the 1^{st} and the 99^{th} percentiles of the pooled distribution. $^{+}$ indicates that statistics are computed over a subset of the entire sample.

Variable	CDP Mean	Plan Mean	No Plan Mean	CRSP/COMPUSTAT Mean	CRSP/COMPUSTAT 95^{th} perc.
Market Value* ($ bn)	21.8	24.0	17.8	3.8	18.4
Total Assets* ($ bn)	38.3	42.9	30.3	7.9	32.8
Total Liabilities* ($ bn)	26.1	29.4	20.4	5.5	22.2
Income B. E. Items* ($ bn)	1.2	1.4	1.0	0.2	2.1
Liabilities to Assets Ratio*	0.6	0.6	0.6	0.7	1.3
ROA*	14.3	14.0	14.9	4.4	71.7
WACC*$^{+}$	8.3	8.1	8.9	8.3	14.1
Altman Z-Score*$^{+}$	3.9	3.9	3.8	3.7	13.5
ESG Score (1)$^{+}$	38.2	38.6	37.4	18.4	49.6
ESG Score (2)$^{+}$	66.8	67.8	65.1	51.4	82.4
ESG Score (3)$^{+}$	5.0	5.1	4.8	4.5	6.2
Emissions* ($mtCO_2$e ml)	5.0	5.7	3.7	-	-
Emissions Intensity*	1.9	2.4	1.0	-	-
Unique Firms	449	256	193	6,051	

pooled means of a selected set of characteristics from CRSP COMPUSTAT, Bloomberg, Thomson Reuters, and MSCI. The average firm in the merged sample (i.e., reporting to CDP) is above the 95^{th} percentile firm in the size distribution of the CRSP COMPUSTAT universe. The firms in the

[12]See *https://www.epa.gov/ghgemissions.*

merged sample also have substantially higher average income than the average firm in the CRSP COMPUSTAT universe, as well as a higher Return on Operating Assets (ROA), but a similar liabilities-to-assets ratio, and a slightly lower probability of bankruptcy.[13]

There is also an interesting distinction between the firms with and without plans for future emissions reduction. Firms which report such plans are on average larger, have higher income, substantially lower cost of capital,[14] and lower probability of bankruptcy than firms which do not report plans. Moreover, plan-reporting firms have greater emissions intensity (as measured by their higher emissions-to-capital ratio) than non-plan-reporting firms. The size, performance, and emissions intensity of firms can affect their incentives to disclose emissions reduction plans, as increases in these attributes can make firms more visible, resulting in greater scrutiny and pressure to disclose.[15]

To verify CDP disclosures, we also acquire, for a subset of firms, their Environmental, Social, and Governance (ESG) rating scores from three separate sources, namely, Bloomberg ESG Data Service, Thomson Reuters Asset 4 ESG, and MSCI ESG, who independently assess firms' performance on carbon emissions and environmental-related activities.[16] Bloomberg, Thomson Reuters, and MSCI report ESG scores for 30%, 17%, and 32% of the pooled CRSP COMPUSTAT sample respectively. Coverage of CDP-reporting firms in our sample, however, is substantially higher (69% in Bloomberg, 57% in Thomson Reuters, and 90% in MSCI respectively). Interestingly, across the three providers, the externally generated ESG rating scores are not hugely higher for firms in CDP than for the average firm in the universe—this raises the possibility that a certain degree of "green-washing" might motivate firms to report. We are careful, therefore, to consider this factor, and to attempt to validate the CDP data along the dimensions in which we are interested, as we

[13]As implied by the Altman (1968) Z-score, an indicator of the probability of a company entering bankruptcy within the next two years, based on financial ratios obtained from 10-k reports.

[14]Weighted Average Cost of Capital (WACC) is a built-in function provided by Bloomberg Equity. For details on the computation of the WACC, we refer to the report in *https : //staffblogs.le.ac.uk/socscilibrarians/files/*2013/05/*wacchelp.pdf*.

[15]Size and performance can also be related to incentives to disclose through common determinants of these variables. For example, firms in CDP have substantially higher fractions of institutional ownership than firms in the universe (82% vs 64%), and we find that firms with plans have slightly higher fractions of institutional ownership than firms without (82 vs 81%). Institutional ownership has been associated both with higher firm value (e.g., McConnell and Servaes, 1990), as well as with pressures for firms to consider environmental issues (e.g., Hoepner et al. [2018] and Dyck et al. [2018]). The CDP selection bias is also documented in Luo et al. [2012].

[16]Despite multiple controversies on ESG rating methodologies (see, for example, Christensen, Serafeim, and Sikochi [2019]), we find that these three different ESG metrics are positively correlated in our sample (74% correlation between Thomson Reuters and Bloomberg, 24% correlation between MSCI and Bloomberg, 34% correlation between MSCI and Thomson Reuters). These providers also make a range of environmental specific indicators available—such as the Emissions Reduction score and the total carbon footprint—which we later use in our analysis.

describe more fully below.

2.3.3 Firms' Actions, Beliefs, and Plans

In this section, we discuss how we use the CDP data to construct three measures that summarize important dimensions in the context of climate risk mitigation, namely, firms' climate mitigation *actions* to date, reflected in their actual changes in carbon footprints; their *beliefs* about the risk of climate-related regulation; and finally, their *plans* for future carbon footprint mitigation activities. We begin by describing the measures that we construct, and discuss how we validate these metrics using a range of internal and external data, including third-party verified indicators of firms' sustainability collected using publicly available sources. Then, we show that firms' plans help to predict their subsequent actions, and we uncover interesting variation along both belief and action dimensions, which we subsequently attempt to rationalize using a theoretical model.

Actions

We measure a firm's "abatement action" in each year as the annual change in its reported carbon emissions. Specifically, we define firm i's *abatement rate* between time t and $t+1$ as:

$$x_{i,t,t+1} = -\left(\frac{Emissions_{i,t+1} - Emissions_{it}}{Emissions_{it}}\right), \tag{2.1}$$

where the variable $Emissions_{it}$ measures firm i's direct emissions from production (scope 1) as well as indirect emissions from consumption of purchased energy (scope 2),[17] as reported in CDP in each reporting year t. We exclude from the study other self-reported indirect emissions from the production of purchased materials, product use etc. (scope 3) as the disclosure quality is low (see, for example, Bolton and Kacperczyk [2019]). In the appendix C we plot carbon emissions disclosures in CDP against third-party estimates provided by Thomson Reuters—to summarize, we obtain consistent figures across the two datasets for the majority of firms in the sample.[18]

Beliefs

In CDP, firms are queried about their exposures to three broad types of risks. The first is risk arising from likely changes in the physical climate, the second is risk arising from future environ-

[17] Disclosures of carbon emissions in CDP follow the Greenhouse Gas Protocol Corporate Standard classification.

[18] For example, in 2017, we are able to match a total of 154 firms out of the 368 firms to the Asset 4 ESG dataset. These firms are spread across sectors. For roughly 85% of these matched firms, we find perfect matches between the two datasets, or discrepancies below 10% of the Asset 4 ESG value. For the remaining observations, CDP disclosures are lower than the Asset 4 ESG estimates, especially in pollution intensive sectors such as Energy and Utility.

mental/greenhouse gas emissions regulation, and the third is risk arising from changes in consumer tastes and social/macroeconomic conditions. We focus on the second type of risk given our interest in the responses of firms to climate regulation events.[19] In CDP, almost 90% of the reporting firms state that they associate climate regulation events with an increase in their operational costs, which in turn may lead to a reduced capacity to conduct "business as usual" operations.

In each reporting year t, firms provide the following pieces of information about the expected impact of a future climate regulation event:

1. An horizon H at which the environmental regulation event is expected to occur.
2. The likelihood of the event q occurring, ranging between *exceptionally unlikely, very unlikely, unlikely, about as likely as not, more likely than not, likely, very likely, virtually certain*, and *unknown*, to which we assign numerical values of 0.01, 0.1, 0.25, 0.5, 0.6, 0.75, 0.9, 0.99, and 0.5 respectively for the purposes of quantitative analysis.[20]
3. The expected magnitude of the impact of the event M, which ranges between *low, low-medium, medium, medium-high,* and *high*, to which we assign values 1, 2, 3, 4, and 5 respectively, as well as *unknown* responses, which we simply replace with the sector specific mean of the impact in each reporting year.

To convert these reported data to a measure of beliefs, we define the expected discounted impact of the regulation event reported by firm i in year t as:

$$\Lambda_{i,t} = \beta^{(H_{it}-t)} M_{it} q_{it}. \tag{2.2}$$

In equation (2.2), β is a discount rate set equal to 0.93, which is the weighted average cost of capital of the representative firm in the CDP sample.[21] In the appendix C, we show the frequency of responses of Λ_{it} at each horizon H_{it}, and the average expected impact (i.e., the $t-$pooled cross-sectional average of M_{it}) reported over the 2011 to 2017 period. The plot shows that the reported event horizon H_{it} ranges between zero years and over ten years from the date of reporting, and

[19] We note that the third category includes potential reputational losses if the firm fails to meet regulatory/substainability objectives. Importantly, as reported in the appendix C, reputational risk is strongly correlated with the regulatory risk reported in firms' disclosures, so our focus on the second source also captures such impacts to an extent.

[20] As a robustness check, the appendix C confirms that excluding *unknown* responses does not alter the empirical findings reported in this section.

[21] We take the full sample mean (2010–2016 accounting period) of the Weighted Average Cost of Capital (WACC) from Bloomberg Equity.

varies considerably across firms. Moreover, the expected impact of the event Λ_{it} increases, on average, with the time horizon of the event T_{it}. In the appendix C, we also regress Λ_{it} on firms' current carbon footprint and current market value, as well as a set of dummy variables to soak up industry, time, and firm headquarter-specific variation. We find that firms' self-reported beliefs about the future risks of climate regulation increase significantly with their current carbon footprint, though they decrease with firm size, controlling for the level of emissions.

In addition to these more structured quantitative assessments, firms also report unstructured text about the *specific form* of climate regulation that they expect. This text information varies with firms' location and industry, as well as varying across time. We provide more detail in the appendix C about these unstructured text disclosures, but highlight here that firms' two most frequently stated types of anticipated climate regulation are, as one might expect, i) a fossil-fuel energy tax, and ii) a carbon tax/levy, generally associated with a cap and trade system. Firms also refer to mandatory emissions reporting programmes as a third category of potential climate regulation. These text disclosures partly motivate our modelling choice, described later, of regulation in the form of a carbon levy.

Plans

We use firms' self-reported emissions reduction targets to construct a proxy for planned future emissions abatement. We note here that some firms report these targets, while others do not, a distinction on which we focus in our subsequent work reported below. The firms that *do* report targets report the following information in each year t:

1. A maturity T by or before which the target is planned to be achieved.

2. The total percentage of carbon emissions in year t that the firm plans to reduce between year t and the target year T, which we denote as $\hat{x}$.

We assume a constant emissions reduction rate between each reporting year t, and the stated target year T, which gives us a present discounted abatement rate (i.e., a *plan* for abatement) for each firm i:

$$plan_{i,t} = \frac{1}{T_{it} - t} \sum_{\tau=t+1}^{T_{it}} \beta^{\tau-t} \hat{x}_{it}, \tag{2.3}$$

where the first timing of abatement $\tau = t + 1$ refers to one year after the year of reporting.[22] In the appendix C, we plot and summarize the various reported components of the abatement plan in equation (2.3). The most frequently reported target horizon is between 1 and 5 years, though some firms report far longer horizons, up to 25 years ahead. As before, the longer the stated horizon, the greater the reported $\hat{x}$, on average across firms and reporting years.

In the appendix C, we also attempt to externally validate these estimates. We do so once again by relying on the subset of reporting firms that are also tracked by Thomson Reuters in their Asset 4 ESG dataset, as well as by MSCI in their MSCI ESG dataset. We plot the environmental score that feeds into the ESG rating (a measure of firms' environmental commitment) in Thomson Reuters and MSCI against our measured $plan_{i,t}$, and find a strong positive relationship between our measure and these two ratings.

2.3.4 Patterns in Firms' Actions, Beliefs, and Plans

Figure 2.2 *Beliefs, Plans, and Actions*

The left plot shows the belief metric as in (2) against reporting years in the CDP questionnaires. The red (black) line refers to firms that disclose (do not disclose) plans in the previous reporting year (initial beliefs are set equal to the average belief observed in the next available year, e.g. in 2012). The right plot shows abatement rates and plans as in (1) and (3) respectively against reporting years in the CDP questionnaires. The red (black) line refers to abatement rates for firms that disclose (do not disclose respectively) plans in the previous reporting year. The red thin line at the top of the right-hand panel shows previous year plans for emissions abatement.

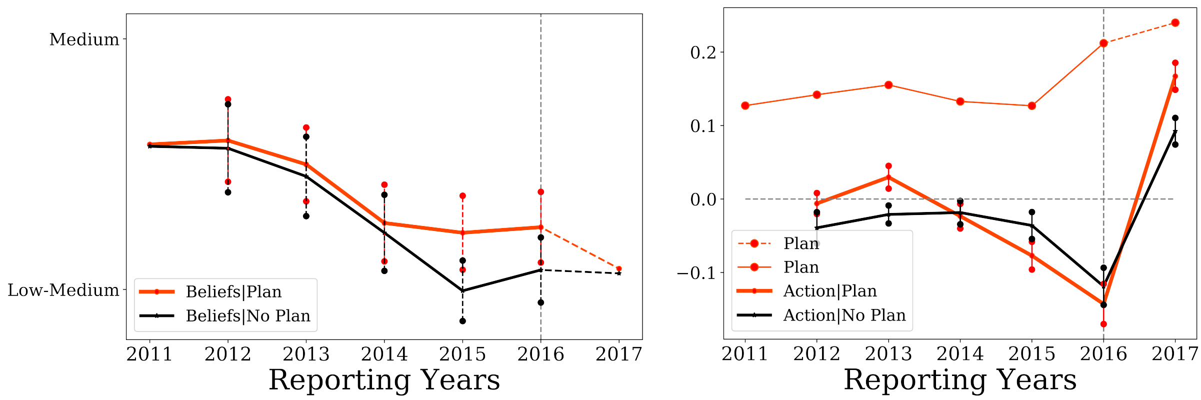


Figure 2.2 plots the beliefs and actions of firms across our sample period, as well as 95 percentile

[22]It is worth noting that CDP questionnaires are released in October of each reporting year, while firms' responses are submitted in June or July of the same year, with exceptions of later submissions. Planned emissions reduction, as reported from firms in the second-half of the year, refer to the year ahead onwards.

confidence intervals across reporting years in the dataset. The left-hand panel of the figure plots conditional averages of beliefs in each reporting period, i.e.:

$$\Lambda_t^p = \frac{1}{N_t^p}\sum_{i=1}^{N_t^p}\Lambda_{i,t}, \quad \Lambda_t^{np} = \frac{1}{N_t - N_t^p}\sum_{i=1}^{N_t - N_t^p}\Lambda_{i,t}, \tag{2.4}$$

where N_t^p is the number of plan-reporting firms, and N_t is the total number of firms in reporting year t.[23] The right-hand panel plots firms' actions (with notation as above):

$$x_{t,t+1}^p = \frac{1}{N_t^p}\sum_{i=1}^{N_t^p} x_{i,t,t+1}, \quad x_t^{np} = \frac{1}{N_t - N_t^p}\sum_{i=1}^{N_t - N_t^p} x_{i,t,t+1}. \tag{2.5}$$

In each plot, the firms that report plans are displayed in red, and those that do not report plans are displayed in black. In the right-hand plot, we also show a thin red line, which plots the average planned abatement rate, i.e., $plan_t = \frac{1}{N_t}\sum_{i=1}^{N_t} plan_{i,t}$ for those firms that report plans.[24]

As described earlier, we construct our measure of beliefs using firms' qualitative responses about the expected impact of future climate regulation. Observed beliefs exhibit a moderate decreasing trend between 2011 and 2015 for all firms (from medium (numerical value 3) to low-medium (2) expected impact across reporting years).[25] Firms that do not report plans exhibit a more pronounced downward slope in beliefs than firms reporting plans for future abatement. This difference is especially pronounced in 2015, the year prior to the announcement of the Paris agreement. In this year, firms with a plan seemingly modulate their belief revisions relative to the firms with plans, who more aggressively downwardly update their beliefs about future climate regulation. This trend reverses following the Paris agreement, when all firms upwardly revise their beliefs about the expected impact of climate regulation. Once again, this belief revision between 2015 and 2016 exhibits differences between the firms with and without plans—firms without plans display a much sharper upward belief revision than those with plans between these two periods.[26]

[23] In the appendix C, we repeat this exercise using a weighted average of firms' beliefs, plans, and actions, where the weights vary with the emission intensity of the firms in CDP, as described in Table 1.

[24] Note here that we simply ignore at this stage the distinction between the size of the emissions reduction that firms plan, and the horizon over which they choose to implement this emissions reduction. We conflate the two into the planned abatement rate in what follows.

[25] In the appendix C, we show that such a decreasing trend is common to both components of the beliefs measure (e.g., likelihood and magnitude of future regulation), meaning that firms are downward adjusting the likelihood of the regulation as well as its expected impact across reporting years.

[26] In the appendix C, we also look at the average stock returns of firms with and without plans in the week surrounding the announcement of the Paris agreement. The results show that while both groups of firms experienced negative stock returns on average, firms without plans were the ones most strongly affected by the announcement.

The right-hand panel of Figure 2.2 shows how the current actions of firms on emissions reduction vary over time, once again splitting firms into two groups based on whether they do or do not report plans for future emissions reduction.[27] The plots show patterns similar to the dynamics of beliefs—both groups of firms increased their emissions, i.e., reduced their abatement activities, between 2012 and 2016, leading up to the Paris climate change agreement. Perhaps surprisingly given their reported beliefs, firms with plans reduced their abatement activities *more* than firms without plans over this period. Once the Paris agreement is ratified, however, both groups sharply reduce their emissions, i.e., increase their abatement activities, in 2017. And clearly, firms with plans increase abatement activities more than firms without reported plans for future emissions reduction.

The plans themselves are plotted as a thin red line in the right-hand panel of the figure. The expected future abatement rate remained steady until 2015, but rose significantly in 2016, predicting the realized spike in emissions reduction in 2017. Importantly, as we show in the appendix C, predicted and realized emissions reductions persist once we disaggregate the representative firm's disclosure at the sector level, though there is variation across sectors. This bolsters the case that the spike observed in the data is a reaction to a global shock of the Paris agreement announcement, rather than a sector-specific regulatory shock.

A note on robustness is in order here. As with many ESG-related datasets, CDP is an unbalanced and expanding panel with few firms at the beginning of the sample and more as time goes on. An issue with such datasets is that results could potentially be driven by composition effects—as from one year to another, firms that are potentially very different from the average sample firm join the panel. For completeness, the appendix C shows the average dynamics of beliefs, actions, and plans for a balanced panel of CDP firms that reported consistently in each year beginning with 2011. The sample shrinks as a result of this filter, so the magnitudes are different. Nevertheless, all of the major patterns identified in Figure 2.2, i.e., the decreasing trend in beliefs, the reaction to the Paris Agreement Announcement, and the more pronounced reaction of firms with plans, are preserved in the restricted sample.

[27] Note that actions, which are percentage changes in total reported carbon emissions, are winsorized between the 5^{th} and the 95^{th} percentiles of the pooled distribution, as summarized in the appendix C.

Next, to better understand the underlying source of these intriguing patterns, we build a dynamic model of firms' carbon emissions reduction.

2.4 A Baseline Dynamic Model of Carbon Emissions Reduction

Our modelling strategy proceeds in two steps. We first begin with a dynamic model of a single representative firm considering its optimal abatement strategy. In a second step, to better model the heterogeneity in responses that we observe across firms with and without plans, we extend the model to a two-firm version with information asymmetry and strategic considerations.

2.4.1 Setup: Single-Firm Model

The economy exists for $t = 0, \ldots, T$ time periods, and we model a single firm operating in this economy. At the beginning of each time period t, the firm operates with a stock of polluting capital k_{t-1}, producing a proportional amount of carbon emissions $\xi_{t-1} = \eta k_{t-1}$ (measured at the end of time period $t-1$). The firm can reduce or increase its emissions at a rate x_t. If the firm decides to abate, the capital stock then has the following law of motion:

$$k_t = k_{t-1}(1 - x_t), \tag{2.6}$$

with corresponding carbon emissions (measured at the end of time period t) of:

$$\xi_t = \eta k_t = \eta k_{t-1}(1 - x_t) = \xi_{t-1}(1 - x_t). \tag{2.7}$$

Over any time period $t < T$, the firm makes profits π_t from its operations:

$$\pi_t = \omega k_t - \frac{1}{2}\phi x_t^2 k_{t-1}, \tag{2.8}$$

where ωk_t is the firm's output from a linear production function (ω is a productivity constant), and ϕ is a quadratic adjustment cost parameter that is affected by the rate of emissions reduction or abatement (we simply normalize the cost of incremental investment to zero).

At time $t = T$, a regulation event occurs with certainty, and the firm pays a carbon levy λ

for each unit of carbon emissions it produces at that time.[28] As a result, the firm's terminal profits can be expressed as:

$$\pi_T^\lambda = \pi_T - \lambda \xi_T. \tag{2.9}$$

The optimal abatement profile $\{x_t\}_{0\leq t\leq T}$ maximizes the firm's value conditional on a given intensity of the levy, λ:

$$V_0^\lambda = \max_{\{x_t\}_{0\leq t\leq T}} \sum_{t=0}^{T-1} \beta^t \pi_t + \beta^T \pi_T^\lambda, \tag{2.10}$$

where β denotes the one-period discount rate of the firm.

For each maturity $0 \leq t < T$, the firm value satisfies the Bellman equation:

$$V_t^\lambda = \max_{x_t} \{\pi_t + \beta V_{t+1}^\lambda\}, \tag{2.11}$$

with the terminal condition:

$$V_T^\lambda = \pi_T^\lambda. \tag{2.12}$$

Solving the Model

In the appendix D, we show the first order condition of the Bellman equation with respect to x_t. The optimal abatement profile conditional on a given intensity of the levy λ is:

$$x_t^*(\lambda) = \beta \left(x_{t+1}^*(\lambda) - \frac{1}{2}(x_{t+1}^*(\lambda))^2 \right) - \frac{\omega}{\phi},\ 0 \leq t < T, \tag{2.13}$$

and the terminal abatement rate is:

$$x_T^*(\lambda) = \frac{1}{\phi}(\lambda \eta - \omega). \tag{2.14}$$

Comparative Statics

The comparative statics of the terminal abatement rate x_T^* in (2.14) are intuitive. The abatement rate increases with the intensity of the levy, λ, as well as with the parameter η, which captures the pollution intensity of the firm. On the other hand, the abatement rate decreases with the productivity of polluting capital, ω. Finally, regardless of whether the model predicts an abatement

[28] In the interests of parsimony and simplicity, we choose to model the carbon pricing mechanism as a tax applied to each unit of emissions produced by the firm. As mentioned in the data section, and as we describe in greater detail in the appendix C, the carbon tax is one of the most frequent types of regulation explicitly mentioned by reporting firms in the data.

or an increase in polluting capital (i.e., regardless of whether $x_T^* > 0$ or $x_T^* < 0$), the magnitude of any abatement decreases as the adjustment cost parameter ϕ rises.

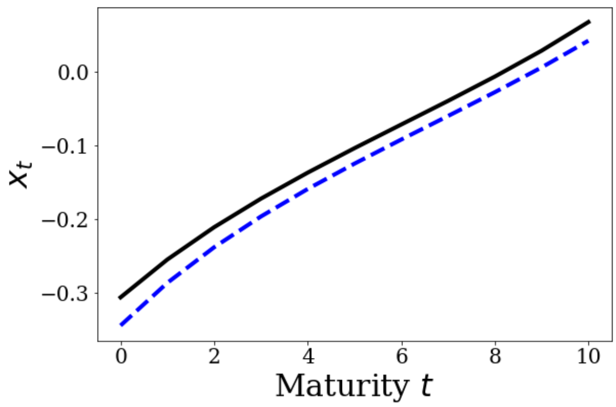
We now outline the key comparative statics of the solution x_t^* in (2.13). First, we can describe how the abatement rate x_t^* varies with maturity t. Let us assume that the levy λ is such that the model predicts abatement (i.e. $x_t^* > 0$) for some maturity $t < T$, then equation (2.13) implies that the abatement rate at the subsequent maturity, x_{t+1}^*, satisifies $x_{t+1}^* > x_t^* > 0$. Iterating this argument up to the regulation event T, we get:

$$x_T^* > x_{T-1}^* > \cdots > x_{t+1}^* > x_t^* > 0, \tag{2.15}$$

that is, an *upward-sloping* term structure of abatement, as seen in Figure 2.3. This result is intuit-

Figure 2.3 *Optimal Abatement Profile*

The plot shows the optimal abatement profile $\{x_t^*\}_t$ as a function of the maturity $t = 0, \dots T$ for two values of the parameter $\lambda = 2.3$ (blue dashed line) and $\lambda = 3.0$ (black thick line) respectively. Other model parameters are: $\phi = 30$, $\omega = 1.0$, $\beta = 0.95$, $\eta = 1.0$, $T = 10$.



ive: the benefits to the firm from an additional unit of polluting capital (given by the productivity parameter ω) accrue at the time at which the capital is in place (i.e., any time t before and including the terminal date), while the costs (the levy λ) are always incurred at the terminal date, and hence always discounted more heavily than the benefits. This gap between the present value of costs and benefits shrinks as we approach the terminal date, resulting in the upward-sloping abatement term structure.

Second, we can fix a maturity t, and see how the abatement rate varies as a function of the levy λ. Assume $t = T - 1$. Substituting the terminal condition (2.14) into (2.13) and computing the second derivative of x^*_{T-1} with respect to λ, we get:

$$\frac{\partial^2 x^*_{T-1}}{\partial \lambda^2} = -\frac{\beta \eta^2}{\phi^2} < 0. \tag{2.16}$$

Equation (2.16) shows that the optimal rate x^*_{T-1} is strictly concave in λ. Equivalently, the firm has a *dampened reaction* to increasing values of the levy. This result holds true if two conditions are satisfied. First, the firm must abate at least some capital in order to control its emissions, and second, abatement of capital must involve convex adjustment costs—these conditions together imply that emissions abatement has convex costs. This result, that the optimal abatement rate is strictly concave in the size of the terminal emissions levy, can be extended by induction to each maturity $0 \leq t < T - 1$. The proof of this result is in the appendix D.

To summarize, this simple first model predicts an upward-sloping term structure of planned abatement (i.e., abatement rates increase up to levy imposition), as the costs of abatement are incurred in the present, but the levy is only incurred at the terminal date, meaning that its impact is diminished by discounting at any intermediate date. Moreover, because of the existence of adjustment costs, the optimal abatement rates are concave in the intensity of the levy for each maturity prior to the regulation event.

It is worth noting that in our model, the only way that the firm can hedge against the regulation event at maturity is to scale back its production at each time period. In particular, our model assumes that the emissions intensity η, which controls the amount of emissions generated per one unit of polluting capital, is constant across time periods. A more complex model would allow the firm to decrease emissions intensity from η_0 to η_τ at some point in time $0 \leq \tau \leq T$, by replacing the old technology with a new one adapted to cleaner standards. Such a second option would likely require the payment of a lump sum for implementing the technology switch.

While we do not solve this more complex model, we do assess how these two emissions abatement options compare using comparative statics. We begin by assuming that the firm has an initial emissions intensity of $\eta_0 = 0.01$mt CO2/\$, and that there is a levy of $\lambda = 100$\$/mt CO2 that needs to be paid after $T = 10$ years. Substituting the optimal abatement rates (2.13) and (2.14) into the expression for the firm value in (2.10), and assuming that $\omega = 25\%$, $\phi = 12$,

$\beta = 0.96$, and $k_0 = 1$ \$BN, we find that firm value at time zero $V_0^\lambda = 1.72$ \$BN, a reduction of roughly 45% with respect to a scenario without regulation, in which $V_0^0 = 3.11$ \$BN.

If the firm could instead reduce its emissions intensity of 20% at some point in time between $t = 0$ and $t = T$, so that $\eta_T = 0.008$, then the firm value under this new scenario would be $V_0^{\lambda'} = 1.92$ \$BN, that is, compared with the capital reduction, the firm would save 0.20 \$BN in total (i.e. 20% of its initial capital). This allows us to understand the costs that firms would be willing to pay for such a technology. In NPV terms, the firm would exercise the technology switch at a time τ, paying a lump-sum investment cost determined by the upper bound $I_\tau = \beta^{-\tau} 0.20$ \$BN.

Single Firm Model Calibration

We calibrate the single firm model to match the average firm in the data. To do so, we make the following parameter choices:

- We set the discount rate $\beta = 0.93$ to match the inverse of the weighted average cost of capital of the representative firm in the dataset.[29]
- We set the maturity of the regulation $T = 10$ to match the first ratification period of the Paris agreement (December 2020), which is the most frequent target year reported by the firms in the dataset.[30]
- We set the initial belief about the intensity of the carbon levy $\lambda_0 = \bar{\lambda}$, where $\bar{\lambda}$ is a parameter to be estimated, and assume that changes in beliefs are a transformed version of the 1 to 5 scale reported in firms' disclosures. That is, we set:

$$\lambda_t - \lambda_{t-1} = m_t \, \sigma^{-1}\Big(\frac{\Lambda_t^p - \Lambda_{t-1}^p}{m_t}\Big), \tag{2.17}$$

where for each reporting period t, Λ_t^+ is the reported belief of the representative firm with a plan in the dataset, $m_t = 1/t$ is a learning parameter, and $\sigma^{-1}(\cdot)$ is the inverse of a sigmoid function.[31] More specifically, we assume that observed revisions are a time-varying function of a regularized signal $\Lambda_t^p - \Lambda_{t-1}^p = m_t \, \sigma\big(\tilde{\epsilon}_t\big)$. We do so to account for the fact that firms

[29]The Weighted Average Cost of Capital (WACC) is a built-in function from Bloomberg Equity.
[30]Note that the reporting period varies between the beginning of 2011 and the end of 2016.
[31]Further details are provided in the appendix D; this simply assumes an update of the prior under Bayesian learning in each period.

report beliefs as categorical variables on the same scale between 1 and 5 each period, and to account for the differential updates conveyed by more extreme reported beliefs as time elapses. The recovered signal $\tilde{\epsilon}_t = \sigma^{-1}\left(\frac{\Lambda_t^p - \Lambda_{t-1}^p}{m_t}\right)$ is therefore what we use in expression (2.17).

- We estimate the parameters $\bar{\lambda}$, ω, and ϕ to minimize the squared distance between the empirical and model-implied abatement actions and abatement plans:

$$\min_{\bar{\lambda},\omega,\phi} \sum_t \left(x_{t,t+1} - x_{t+1}^*(\lambda_t)\right)^2 + \left(plan_t - plan_t^*(\lambda_t)\right)^2, \tag{2.18}$$

where the levy λ_t follows (2.17), $x_{t+1}^*(\lambda_t)$ is the optimal abatement rate at the shortest maturity, computed as in (2.13) and conditional on the belief λ_t, and the optimal plan is the sum of future discounted optimal abatement rates, i.e., $plan_t^*(\lambda_t) = \sum_{\tau=t+1}^{T} \beta^{\tau-t} x_\tau^*(\lambda_t)$.[32] It is worth recalling that, from the specification of the firm's emissions in (2.7) and the capital stock dynamics in (2.6), we have that $x_{t+1}^* = -\left(\frac{\xi_{t+1}-\xi_t}{\xi_t}\right)$, which allows for a direct comparison with the relative change in realized emissions $x_{t,t+1}$, measured as in (2.1) for the representative firm with plans in the dataset. In the same way, the model-implied abatement plan ($plan_t^*(\lambda_t)$) also allows for a direct comparison with the measured abatement plan $plan_t$ in (2.3), reported by the representative firm at year t and anticipating relative changes in emissions from year $t+1$ onwards. Finally, we normalize the emissions intensity $\eta = 1$; we discuss its economic interpretation below.[33]

As reported in Table 2.2., we estimate parameters $\bar{\lambda} = 2.64$ and $\omega = 0.28$. In relative terms, the baseline model therefore estimates that the gross benefit from an additional unit of polluting capital, evaluated at each time period, is roughly 11% of its terminal cost (i.e. $\omega/\bar{\lambda} = 0.11$).

In terms of magnitudes, we note that the productivity constant ω is estimated as roughly twice the ROC of the representative firm with plans in the dataset (i.e., equal to 14.7% as summarized in Table 2.1.).[34] For a normalized emissions intensity $\eta = 1$ per mtCO2\$, the model estimates an initial levy of $\bar{\lambda} = 2.64\$/\text{mtCO}_2\text{e}$. If one had to use a realistic value for the emissions intensity

[32] We impose full consistency between reported plans and actions in CDP, simply excluding the possibility of cheap talk equilibria in our setting (see, for example, Hämäläinen and Leppänen [2017]. More specifically, we assume that the firm can only truthfully report its abatement plan in CDP. One way to justify this choice is to assume that, as in reality, the informational quality of the announcement is subject to a high degree of third-party scrutiny.

[33] The emissions intensity enters the model only at maturity, as $\eta\lambda$. Therefore, the parameters λ and η cannot be uniquely identified in the estimation.

[34] This high and unrealistic value of ω is a feature of this simpler model; the more complex two-firm model delivers a more realistic magnitude of 0.19.

($\eta \approx 0.002$ mtCO$_2$e/\$ from Table 2.1.), the estimated levy would be $\bar{\lambda} \approx 1,320$\$/mtCO$_2$e, incurred at maturity T, which in turn corresponds to an equivalent per-period levy of $\bar{\lambda}^{eq} \approx 87$\$/mtCO$_2$e at each time t.[35]

Despite the growing literature dedicated to the topic, there is still large uncertainty about the social costs of climate change, and the economic implications of carbon policies (see, for example, Nordhaus [2014]). Recent work by Barnett et al. [2020] attempts to quantify the limitations of such uncertainty in terms of discounts applied to the social cost of carbon (SCC), showing that uncertainty-adjusted SCC are substantially lower than average estimates predicted by a set of models in the literature. In a review by Tol [2011], the average of SCC estimates across over 300 published articles is over 150\$/mtCO$_2$e, while the mode of the distribution is below 50\$/mtCO$_2$e. We contribute to this literature using our simple model, which predicts that the representative disclosing firm's actions are consistent with an expected policy of 87\$/mtCO$_2$e, well above, for example, the 30\$/mtCO$_2$e implied levy currently traded in the European cap and trade market.[36] Importantly, to the extent that our estimates are credible, the policy implication is that raising the levy substantially might not come as a shock to firms given these implied priors.

Finally, we note that the parameter $\phi = 16.2$, which controls the capital adjustment cost is slightly higher the standard estimates provided by production-based asset pricing models (see, for example, Liu, Whited, and Zhang [2009], where $\phi \approx 12.5$).

Figure 2.7 shows the optimal emissions path $\{\xi_t(\lambda^{eq})\}_{t=1,\ldots 10}$ generated by the estimated model parameters for two values of the per-period levy, namely, $\lambda^{eq} = 85$\$/mtCO$_2$e (dashed red line) and $\lambda^{eq} = 125$\$/mtCO$_2$e (dashed blue line) respectively, assuming initial emissions $\xi_0 = 1$.[37] As the figure shows, increasing the levy from 85 to 125\$/mtCO$_2$e generates an additional 26% decrease in emissions (from the 25% decrease under a 85\$/mtCO$_2$e levy). Moreover, consistent with the theoretical predictions of the model, the figure shows that most of the abatement occurs at later maturities, when the time horizon approaches the regulation event.

[35] The equivalent levy is simply measured by $\lambda^{eq} = \frac{\beta^T \bar{\lambda}}{\sum_{t=1}^{10} \beta^t}$, for the discount rate $\beta = 0.93$.

[36] Information on the current pricing of carbon in the EU emissions trading scheme (EU ETS) can be found at *https : //ec.europa.eu/clima/policies/etsen.*

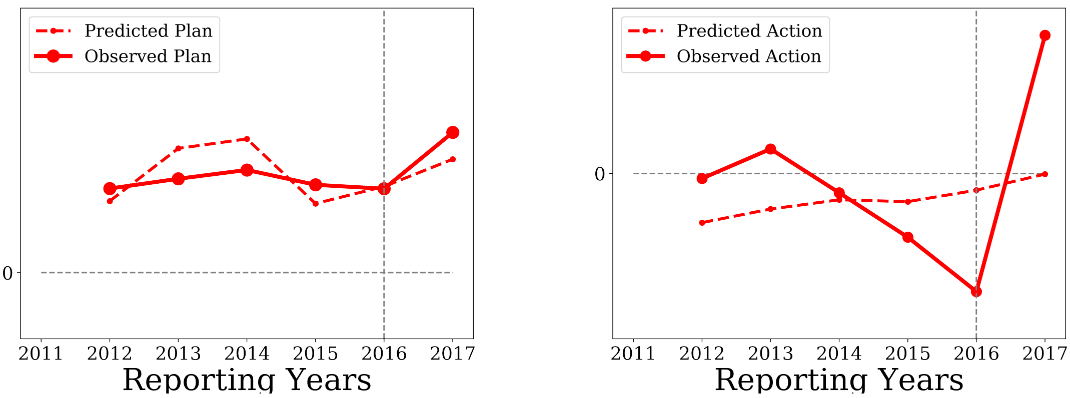
[37] According to recent academic studies (see Carleton and Greenstone [2021]), a social cost of carbon updated to the frontier of economic and climate science would average around 125\$/mtCO$_2$e.

To assess the predictive quality of the model, the left-hand panel of Figure 2.4 compares empirical and model-implied abatement plans on average across the sample period, while the right-hand panel compares the model-implied actions with observed abatement actions on emissions reduction. In both plots, the model-implied moments are dashed lines, while the solid lines show the patterns in the data.

The model-implied abatement plans and actions vary for two reasons. The first is that the impending regulation event gets closer as time passes and $T - t$ falls. The second is that we feed the model the reported beliefs over the timing and intensity of the levy, i.e., the model takes as an input Λ_t reported in the data.

Figure 2.4 *Model-Implied and Observed Moments*

The left plot compares the model-implied and observed abatement plan against reporting years in CDP. The right plot compares the model-implied and observed abatement rate against reporting years in CDP. Thick (dashed) lines refer to observed (model-implied) moments. Model parameters are reported in the first column of Table 2.2..



The left-hand panel of Figure 2.4 shows that the model captures the dynamics of plans reasonably well, once the beliefs have been inputted into the model. While there is an issue of magnitude, which might be expected given the simplicity of the model, the broad patterns are roughly similar to the data. However, the right-hand panel of the figure shows that model-predicted abatement actions miss important dynamics in the data on the average firm's abatement actions. Moreover, the data that we match only comprises the firms who do report plans, rather than the firms that do not, and as we showed in Figure 2.2, firms with and without plans exhibit noticeable differences in behavior. To attempt to better explain the patterns in the data, we therefore move to a model with two firms, which we describe in the next section.

2.5 A Leader-Follower Model of Carbon Emissions Reduction

To improve the predicted dynamics of the model, and to more broadly capture the patterns observed in the data, we introduce a *second* firm in the market to represent the firms that *do not report* plans for emissions reduction. Throughout this section, we denote by l (for *leader*) and f (for *follower*) the firms with and without plans for emissions reduction respectively, and we derive l and f's optimal abatement profiles in an extended Stackelberg leadership equilibrium where l (the firm reporting its plans) announces commitment to an abatement plan before the Stackelberg game is played, rationally anticipating the abatement choices of the competitor, while f (the firm not reporting its plans) infers information from the leader's announcement, and takes the abatement choices of the leader as given.

2.5.1 Setup: Two-Firm Model

We add strategic considerations to the environment as follows:

- In each time t, we augment the baseline profit function in ((2.8)) with a *payoff externality* that makes firm l and firm f's profits depend *symmetrically* on the other firm's actions.

$$\pi_t^l(x_t^f) = \omega k_t^l - \frac{1}{2}\phi(x_t^l)^2 k_{t-1}^l - \gamma_t x_t^f (k_t^l - k_{t-1}^l), \tag{2.19}$$

$$\pi_t^f(x_t^l) = \omega k_t^f - \frac{1}{2}\phi(x_t^f)^2 k_{t-1}^f - \gamma_t x_t^l (k_t^f - k_{t-1}^f), \tag{2.20}$$

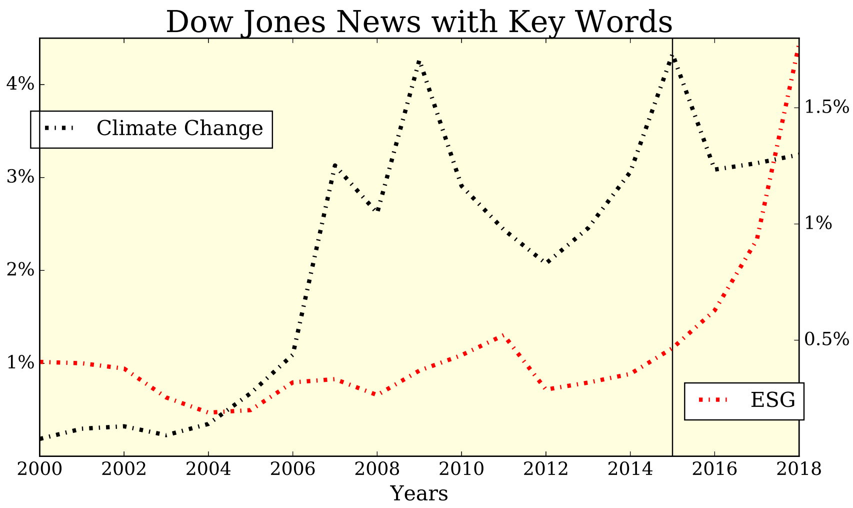
  when γ_t is positive, this can be interpreted as a *reputation externality*, in that a firm's profits are reduced in any period t in which the *other* firm abates emissions. γ_t can also be thought of the degree of attention paid by society to firms' abatement activity, manifested in relative performance evaluation along this dimension.[38] The dynamics of media attention to firms' ESG scores has been increasing, even relative to attention paid to general climate change issues. Some evidence to support this assumption can be seen in Figure 2.5, which documents the frequency of articles in Dow Jones newswire on selected keywords, but also directly from

[38]The externality γ_t is a reduced-form attempt to capture the level of attention paid by society to firms' carbon emissions reduction activities, in a manner that explicitly compares firms' performance along this dimension. Put in these terms, it is worth noting that we could simply set $\gamma_t = \gamma$, that is, a constant time-path of attention paid by society to firms' abatement activity, and still get all of the results developed in this section. However, as we discuss later, allowing for a non-constant time-path improves the fit of the model, and more importantly, provides additional interesting predictions about the time-path of firms' abatement plans.

firms' unstructured disclosures about climate change risks.[39]

Figure 2.5 *Historical Environmental Media Coverage*

The figure shows the time-series of the percentage of Dow Jones articles containing the words *"Climate Change"* (black dotted line) and *"ESG"* (red dotted line) in headlines or lead paragraphs as recorded from the Factiva database between 2000 and 2018.



- We also introduce an asymmetry in the degree of *information* over the intensity of the levy. Specifically, we assume that only firm l receives information about the true intensity λ of the levy, which we now model as:

$$\lambda = \bar{\lambda} + \tilde{s}. \tag{2.21}$$

In contrast, firm f can only observe the expected value $\bar{\lambda}$ of the levy. This second assumption requires further justification, which we attempt to provide in the appendix D; we summarize a few of these arguments below.

Before doing so, we note that in the model, as a result of its superior information over the levy, firm l has a timing advantage over firm f, because it can perfectly anticipate firm l's actions before the game is played. Specifically, when deciding its optimal course of action, firm l can perfectly anticipate firm f's reaction to both its actions and to the public component of the levy, $\bar{\lambda}$. In contrast, firm f takes firm l's actions as given, and reacts only indirectly to the private signal of the levy, $\tilde{s}$.

[39]For example: "Failure to meet investors' expectations [..] could result in a risk to corporate reputation, with incremental financial impact given the expanding role of Environmental, Social and Governance (ESG) issues in evaluations."

In our data, firms with plans have lower financial leverage and higher profitability, on average, than firms with plans. A plausible assumption here is that attention is a scarce resource, and attention paid by the firm to financial stakeholders takes away from sustainability activities that are more likely to appeal to other stakeholders. If this is the case, then less profitable firms will need to spend more time focusing on the needs of financial stakeholders. In contrast, more profitable firms will pay more attention to the details of climate regulation, appeal to non-financial stakeholders by activities such as publishing plans, and potentially have more precise forecasts. Moreover, we find that plan-reporting firms are on average more carbon intensive than firms with no plans. This makes them more exposed to the climate regulation (this can also be seen in firms' own disclosures of climate regulation risk in 2.2). This also, we believe, gives them greater incentives to focus on the details of regulation.

Second, we find direct evidence from the CDP disclosures that firms with plans are different in another relevant manner to firms that do not report plans. In particular, firms with plans have a greater propensity to a) engage with policymakers, and b) provide direct funding to climate regulatory activities. This proximity to the policy process is another channel supporting the second assumption made above (see, for example, recent work in Ovtchinnikov et al. [2019], Zhang et al. [2019], and Heitz et al. [2019]).

In what follows, we derive the optimal abatement profiles of the two firms in a Stackelberg duopoly game. Before proceeding further, we note that we do not endogenize the timing of the actions in the game, meaning that we do not formally prove optimality of the leadership equilibrium. However, we do show in the appendix D that a simultaneous equilibrium with no plan revelation by the leader does a worse job of describing the patterns in the data, even when we allow for different adjustment costs of emissions abatement as a more traditional source of heterogeneity in the observed patterns of beliefs and actions across firms. We now move to discussing equilibrium in the two-firm model.

Equilibrium Abatement Profiles

Holding fixed the model parameters $\{\phi, \beta, \eta, \omega, \bar{\lambda}, \tilde{s}\}$, and the maturity of the regulation event T, for any time $t \leq T$ and payoff externality $|\gamma_t| \leq \frac{\phi}{\sqrt{2}}$, the optimal abatement profiles x_t^l and x_t^f satisfy: [40]

[40] The upper bound on the magnitude of the strategic parameter γ_t is a requirement that we impose to get well-defined abatement plans and actions. This can be thought of as a bound on the size of the reputation externality.

Firm f (follower):

$$x_t^{*,f} = w_t x_t^{*,l} + \beta\Big(x_{t+1}^{*,f} - w_{t+1}x_{t+1}^{*,l} - \frac{1}{2}(x_{t+1}^{*,f})^2\Big) - \frac{\omega}{\phi}, \tag{2.22}$$

with $w_t = \frac{\gamma_t}{\phi}$, and,

$$x_T^{*,f} = w_T x_T^{*,l} + \frac{\eta}{\phi}\bar{\lambda} - \frac{\omega}{\phi}. \tag{2.23}$$

Firm l (leader):

$$\begin{aligned} x_t^{*,l} = \frac{\beta}{(1-2w_t^2)}\Big(x_{t+1}^{*,l}(1 - w_{t+1}^2 - w_t w_{t+1}) + x_{t+1}^{*,f}(w_t - w_{t+1})\ldots \\ \cdots - \frac{1}{2}((1-2w_{t+1}^2)(x_{t+1}^{*,l})^2 + w_t(x_{t+1}^{*,f})^2)\Big) - \frac{\omega(1+w_t)}{\phi(1-2w_t^2)}, \end{aligned} \tag{2.24}$$

and

$$x_T^{*,l} = \frac{\eta}{\phi}\Big(\bar{\lambda}\frac{1+w_T}{1-2w_T^2} + \tilde{s}\frac{1}{1-2w_T^2}\Big) - \frac{\omega(1+w_T)}{\phi(1-2w_T^2)}. \tag{2.25}$$

The derivations of these expressions are in the appendix D.

Comparing the Single-Firm and Two-Firm Models

We now compare the equilibrium abatement rates in the expressions above in the previous subsection with the baseline solution established in (2.13) and (2.14). We first state the following proposition:

- **Proposition 1.** *At T, the date of the regulation event, for any given set of model parameters $\{\phi, \beta, \eta, \omega, \bar{\lambda}, \tilde{s}\}$ and payoff externality $|\gamma_t| \leq \frac{\phi}{\sqrt{2}}$, the leader firm l's reactions to changes in the expected carbon levy $\bar{\lambda}$ are larger than those of follower firm f.*
  - **Corollary 1.** *When the payoff externality $\gamma_t \in (0, \frac{\phi}{\sqrt{2}})$, then the leader and follower firm reactions to the levy are both greater than their corresponding reactions in the baseline (i.e., single-firm) model with no cross-firm payoff externalities.*

The proof of this proposition can be found in the appendix D. There, we also identify a sufficient condition under which the proposition can also be extended to shorter maturities, i.e., $t \leq T$.[41]

[41] Due to the presence of convex adjustment costs, the result does not necessarily hold for shorter maturities $t \leq T$. However, as we show in the appendix D, Proposition 1 holds at shorter maturities t for the subset of model parameters $\{\phi, \beta, \mu, \omega, \bar{\lambda}, \tilde{s}\}$ and γ_t that generate negative abatement rates (i.e., $x_{t+1}^{*,l}, x_{t+1}^{*,f} < 0$) in equilibrium. Importantly, this inequality is almost always satisfied in the data.

To develop intuition, we begin by discussing the corollary, which is easy to verify—starting from the explicit expressions for the terminal abatement rates in (2.23) and (3.18), one can easily derive that the parameter $\bar{\lambda}$ has a higher marginal effect on $x_T^{*,l}$ and $x_T^{*,f}$ than on the baseline solution x_T^* in (2.14). The intuition is that the cross-firm reputational externalities make firms endogenously increase their reaction to changes in the policy, because the way the model is set up in equations (2.19) and (2.20), firms have incentives *to act alike* provided that γ_t is *positive*. More specifically, when γ_t is positive, firms find more costly to act such that $x_T^{*,f} x_T^{*,l} < 0$. This tendency towards similarity amplifies their actions relative to the "atomistic" optimum which is unencumbered by such externalities.

The proposition says that as the leader internalizes the marginal effect of the parameter $\bar{\lambda}$ on the follower's abatement choice, it reacts *more* than the follower to variations in $\bar{\lambda}$. Why is this the case? Inspecting equations (2.19) and (2.20), we can see that they bear a resemblance to the expressions that one might get from a traditional Stackelberg duopoly, with a modified "demand function of abatement."[42] Essentially, since firm profits respond to (own and other firm) abatement negatively in a similar way that price responds to demand in the traditional Stackelberg model, the leader firm has an incentive to grab "abatement market share" in a similar way to the traditional Stackelberg model, since it has a first-mover advantage.

Another important observation that emerges from the terminal abatement rates in (2.23) and (3.18) is that the leader endogenously puts more weight on the expected component of the levy, $\bar{\lambda}$, than on the private component of the levy, $\tilde{s}$. This is because the leader internalizes the follower's reaction to the movements in the expected levy $\bar{\lambda}$, because both the follower and the leader fully observe $\bar{\lambda}$.

Together with the results stated in Proposition 1, this property predicts interesting relationships between the leader's and follower's reactions to variations in the true value of the levy. For example, think of a situation in which there are shocks to both $\bar{\lambda}$ and $\tilde{s}$ which are equal, but opposite in sign, meaning that the total levy λ remains unchanged. Since the leader firm overweights $\bar{\lambda}$ changes over changes in $\tilde{s}$, and reacts more to changes in $\bar{\lambda}$ than the follower firm, the prediction from the

[42]To see this, note that we can rewrite the firms' terminal profits as:

$$\pi_T^i(x_t^{-i}) \approx (\eta\lambda_i - \frac{\phi}{2}(x_T^i - 2w_T x_T^{-i}))x_T^i - \omega x_T^i \tag{2.26}$$

with $i = l, f$ and $-i = f, l$ respectively.

model is that the leader will react more than the follower to this shock ex-post, even though the leader knows that the change in λ is zero. This prediction wouldn't hold in an environment in which there were payoff externalities as in this model, but no information asymmetry across the two firms.

In the appendix D, we describe an additional feature of the model, and prove a second Proposition 2 there as well. The proposition allows us to understand how the abatement term structure is affected by changes in the time-path of γ_t. While we leave the details to the appendix D, in intuitive terms, Proposition 2 states that when the reputation parameter γ_t decreases monotonically and sufficiently quickly with time, the equilibrium solutions in (2.22) and (2.24) can support an inverted term-structure of abatement, i.e., abatement can decrease over time rather than increase, as in the baseline model. This is because a decreasing time-path of the reputational externality (which might be induced by a sudden increase in attention to climate change which gradually revert back to the mean) introduces an additional cost associated with carbon emissions that accrues more aggressively at the (current) time at which the capital is in place. As we discuss in the appendix D, Proposition 2 can help to reconcile the observed differences between firms' reported abatement plans and actions before and after the announcement of the Paris agreement.

Two-Firm Model Calibration

We conclude this section by calibrating the two-firm model to the data. We begin with the same set of calibrated parameters β and T, while we estimate the remainder of the parameters to satisfy the following minimization problem:

$$\min_{\gamma,g,\bar{\lambda},\omega,\phi} \sum_t \left(x^l_{t,t+1} - x^{*,l}_{t+1}(\lambda^l_t)\right)^2 + \left(plan_t - plan^*_t(\lambda^l_t)\right)^2 + \left(x^f_{t,t+1} - x^{*,f}_{t+1}(\lambda^f_t)\right)^2. \tag{2.27}$$

In equation (2.27), for the purposes of estimation, we specify the sign and magnitude of the payoff externality for each maturity s and reporting year t assuming a simple exponential functional form, i.e., $\gamma_{s,t} = \gamma e^{-g(s-t)}$. The strategic parameter ρ identifies the size of the positive information externality in the model.[43] The beliefs λ^l_t and λ^f_t follow the dynamics:

$$\lambda^l_0 = \bar{\lambda}, \quad \lambda^l_t - \lambda^l_{t-1} = m_t\, \sigma^{-1}\left(\frac{\Lambda^p_t - \Lambda^p_{t-1}}{m_t}\right) \tag{2.28}$$

[43] To preserve consistency with Bayes rule, we impose a zero lower-bound on the value of this parameter.

and:

$$\lambda_0^f = \bar{\lambda}, \quad \lambda_t^f - \lambda_{t-1}^f = m_t\, \sigma^{-1}\left(\frac{\Lambda_t^{np} - \Lambda_{t-1}^{np}}{m_t},\right) \tag{2.29}$$

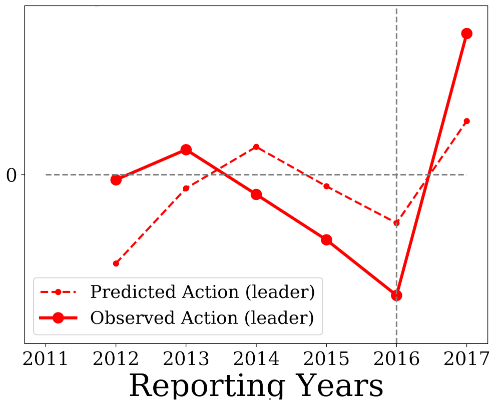
where Λ_t^p and Λ_t^{np} are computed as described in (2.2) using the CDP data, and refer to the beliefs inferred from the data for firms with and without plans in the dataset. Finally, for each reporting year t, the leader's private signal about the levy $\tilde{s}_t$ is extracted from the leader's and the follower's beliefs as:

$$\tilde{s}_t = \lambda_t^l - \lambda_t^f. \tag{2.30}$$

Figure 2.6 summarizes the results of the calibration; the list of input parameters is reported in

Figure 2.6 *Model-Implied and Observed Moments*

The left plot compares the model-implied and observed abatement actions for the leader firm against reporting years in CDP. The right plot compares the model-implied and observed actions for the follower firm against reporting years in CDP. Thick (dashed) lines refer to observed (model-implied) moments. Model parameters are reported in the second column of Table 2.2..



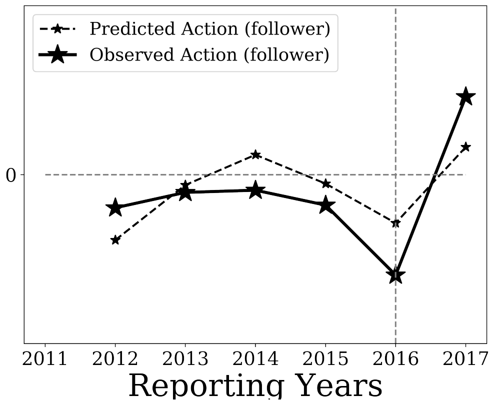


Table 2.2.. The left and right-hand panels in Figure 2.6, show that the more complicated two-firm model with cross-firm externalities and leader-follower dynamics does result in a better ability to capture the observed dynamics of abatement in the data.

Figure 2.6 shows that introducing the strategic parameters γ and g improves the fit of the model.

A few features are worth discussing in this context. The parameters $\gamma = 17.9$ and $g = 0.41$ show that the data are consistent with the presence of a positive reputation externality, whose size decreases with time. As discussed earlier, in the appendix D, we show that when γ_t is positive and satisfies a decreasing condition of this type, the model can generate a downward sloping term-

Table 2.2. *Calibration Results*

The table reports the calibration results for the single-firm (column I) and two-firm (columns II) models respectively. The first set of parameters are calibrated on the representative firm reporting in CDP. The second set of parameters is estimated so that to minimize the sum of squared distances between observed and model-implied abatement rates and actions in the baseline and two firm models (eq. 2.18 and 2.27 respectively). The third set of parameters is estimated so that to minimize the sum of squared distances between observed and model-implied abatement rates and actions in the two-firm model (eq. 2.27).

Parameters	I	II
T	10.0	10.0
β	0.93	0.93
ϕ	16.2	27.0
$\bar{\lambda}$	2.64	2.60
ω	0.28	0.19
g	0.00	0.41
γ	0.00	17.9

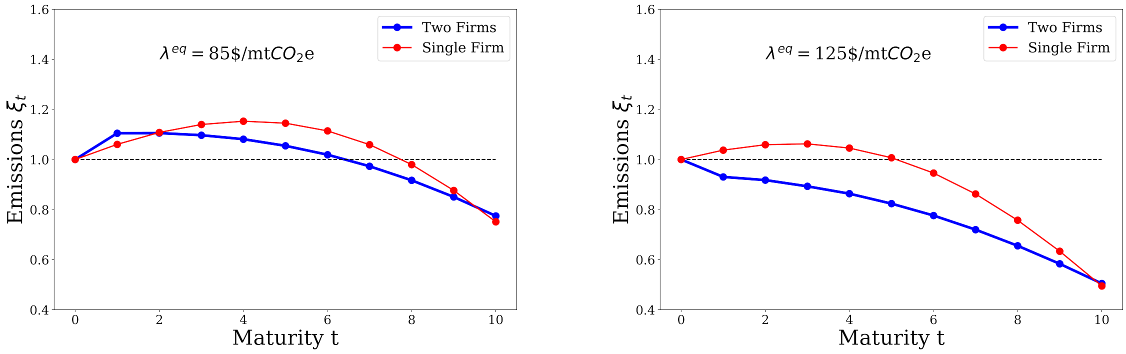
structure of abatement, i.e., firms will find it optimal to abate the most at the shortest maturities. This feature can clearly be seen in the simulation exercise reported in Figure 2.7 and we discuss it in greater detail below.

As reported in Table 2.2., the estimated parameters are $\bar{\lambda} = 2.60$ and $\omega = 0.19$. In relative terms, the model estimates that the gross benefit from an additional unit of polluting capital, accrued at each time period is roughly 8% of its terminal cost (i.e. $\omega/\bar{\lambda} = 0.08$). In terms of economic magnitudes, the productivity constant ω estimated in the two-firm model is far closer to the Return on Operating Capital observed for the representative firm with plans in the dataset, while the parameter ϕ is higher than the reference estimates for capital adjustment costs in the literature. At the same time, the parameter $\bar{\lambda} = 2.60$ implies a per-period levy of $\bar{\lambda}^{eq} \approx 85$ \$/mtCO_2e, as opposed to $\bar{\lambda}^{eq} \approx 87$ \$/mtCO_2e from the baseline model, meaning that the inferences on firms' priors about the levy are very similar from this model.

In addition to the baseline parameters, the model estimates an additional time-varying benefit (cost) from abating (increasing) emissions, which is controlled by the reputation externality term

Figure 2.7 *Optimal Emissions Path*

The plots show the optimal path of carbon emissions at each time period as generated from the baseline model (red) and two-firm model (blue) respectively. Left and right plots refer to the emissions generated by the models when the levy parameter $\bar{\lambda} = 2.6$ and $\bar{\lambda} = 3.83$ respectively, which correspond to an equivalent per-period levy of $\bar{\lambda}^{eq} = 85\$/\text{mtCO}_2\text{e}$ and $\bar{\lambda}^{eq} = 125\$/\text{mtCO}_2\text{e}$ respectively, as specified in Section 4. The remainder of model parameters in input are reported in Table 2.2..



$\gamma e^{-gt} x_t^f x_t^l$. For example, assume that at $t = 0$ the follower firm abates emissions by an amount $x_0^f = 1\%$. For a corresponding abatement (increase) in emissions $x_0^l = \pm 5\%$, the leader firm faces an externality term $\pm \gamma x_0^f x_0^l = \pm 0.009$, which accounts for almost 5% of the output-capital ratio ω. Finally, the estimated rate of decay of this externality $g = 0.41$ implies that the impact of the externality becomes negligible after $t = 2$ or 3 time periods (years in our setup), depending on the magnitude of the competitor's abatement rate.

Figure 2.7 shows the optimal emissions path for the leader firm $\{\xi_t^l(\lambda^{eq})\}_{t=1,\ldots 10}$ generated by the estimated model parameters for two values of the levy in input, $\lambda^{eq} = 85$ \$/mtCO$_2$e (thick red line) and $\lambda^{eq} = 125$ \$/mtCO$_2$e (thick blue line) respectively, assuming initial emissions $\xi_0 = 1$.[44] Here, increasing the levy from 85 to 125 \$/mtCO$_2$e generates an additional 27% decrease in final emissions (from the 23% decrease under a 85 \$/mtCO$_2$e levy), which is a slight amplification in the aggregate response to the policy relative to what is predicted by the baseline model.

Importantly, however, under the most stringent policy, the two-firm model predicts a substantial amplification of the firm's baseline reaction to the policy in the short run. Consistent with the theoretical predictions of the two-firm model, under a positive and time-decreasing payoff extern-

[44] To permit comparison with the single firm model, we assume that the signal $\tilde{s} = 0$

ality, firms decreases in emissions in this extended model primarily occur at the shortest maturity, which is arguably better for the environment.

Although the model mechanism of reputational externalities is able to match the main patterns identified in the data, we cannot rule out the possibility that alternative mechanisms could match those patterns equally well. Two such plausible alternative mechanisms might include: i) managerial incentive schemes set by shareholders (e.g. so-called extrinsic motivations as in Ariely, Bracha, and Meier [2009] such as monetary rewards/penalizations in case of overcompliance/undercompliance with climate regulations; ii) technology shocks induced by the enactment of the policy (e.g., redirected technical change as in Acemoglu, Akcigit, Hanley, and Kerr [2016]), with potentially different effects depending on the firms' original investment opportunity sets.

We note here that for a mechanism as in i) to generate a similar amplification effect as the one predicted in our model, it must be that the firm's shareholders expect undercompliance with the regulatory policy in absence of the monetary incentive, and that such beliefs are consistent with the cross-firm patterns observed in the data. Put differently, such a mechanism requires an additional free parameter which captures time-variation in shareholders' beliefs.

On the other hand, a more complex technological structure of the model as in ii) could likely serve as a substitute for the reputation externality in matching the time-series dynamics in the model. While the Paris Agreement shock might eventually induce preemption in firms' optimal timing of adoption of clean technologies, the market for such technologies experienced a broad slowdown in the years preceding the Paris Agreement announcement (see, for example, the study in León, Bergquist, Wunsch-Vincent, Xu, Fushimi, et al. [2018]).[45] Moreover, such preemption effects would still incur well-documented time lags[46] between the implementation of research and development investments, the issuance of new patents, and the effective adoption of new technologies.[47] Despite these arguments, we nonetheless acknowledge here that our posited mechanism could easily map to an explanation that delivers isomorphic predictions.

[45]See also the green growth statistics from the OECD database. A summary of the slowdown in US green innovation can be found in the OECD report *Green Growth Indicators, 2017.*

[46]See, for example, the review in Hoppe [2002]

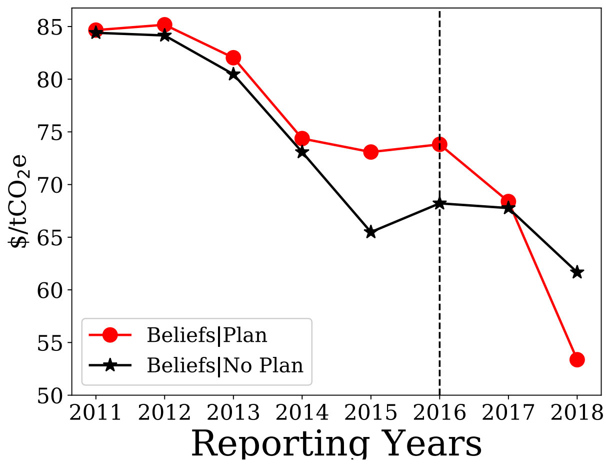
[47]It is also worth mentioning that when we look directly at firms' own disclosures about investment opportunities related to different types of climate change risks (reported in the appendix C), we find no substantial revisions in beliefs about these opportunities in the years preceding the Paris Agreement.

2.6 Out of Sample Predictions

One way to evaluate the model is to assess the quality of its out-of-sample predictions. We therefore extend and process the CDP dataset after estimating the model up to 2017, to include U.S. public firms' responses for the years 2018 and 2019.[48] This period is particularly interesting, as it allows us to evaluate the impact on firms' responses of a regulatory shock that goes in the opposite direction to those used to fit the model, namely, U.S. President Donald Trump's announcement to pull back from the Paris Agreement, which occurred in June 2017.

Figure 2.8 *Extended Beliefs*

The plot shows the belief metric as in (2) against reporting years in the extended CDP questionnaires. The red-circle (black-star) line refers to firms that disclose (do not disclose) plans in the same reporting year.



The left-hand panel of Figure 2.8 shows beliefs computed from the extended CDP dataset that we use as input variables to our out-of-sample evaluation exercise. As can be seen in the figure, in the year following Trump's pull-back announcement, all firms significantly downgrade their expectations of the impact of climate policy regulation. In contrast with the patterns previously observed, however, firms reporting plans for future emissions abatement now appear to revise their beliefs about the intensity of future climate regulation far more extensively than those not reporting plans in response to the announcement. According to the model, the expected impact of climate regulation disclosed by plan-reporting firms decreases by more than 15\$/mtCO_2e relative to their prior

[48]Over these two years, CDP implemented a set of changes to make the questionnaires more aligned with the recommendations of the Task Force on Climate-Related Financial Disclosures (TCFD), which was established in 2016. In the appendix E we report the major changes to the responses and format arising from these changes and how they affected the measures that we compute. We also describe in the appendix E a few adjustments to the data that we needed to implement to conduct the out-of-sample exercise.

estimates, reaching an equivalent per period levy of roughly 55\$/mtCO_2e.

The right-hand panel of Figure 2.8 shows another interesting observation from the new disclosure data, which is the change in the distribution of firms' reported time horizon T over which they expect to reduce emissions. Following Trump's pull-back announcement, in addition to their changing beliefs about the intensity of regulation, firms also seem to change the expected time horizon over which climate regulation is expected to come into effect, by a median value of 2 years.

To conduct the out-of-sample exercise, we use the beliefs reported in the right panel of Figure 2.8 to generate emissions abatement plans and actions from the two-firm model. We also fix all parameter values at the levels reported in the second column of Table 2.2., estimated over the period from 2011 to 2017, except for the time horizon T, which we alter from 10 years to 12 years to account for the evidence seen in Panel B of Figure 2.8 on firms' extended time horizons.

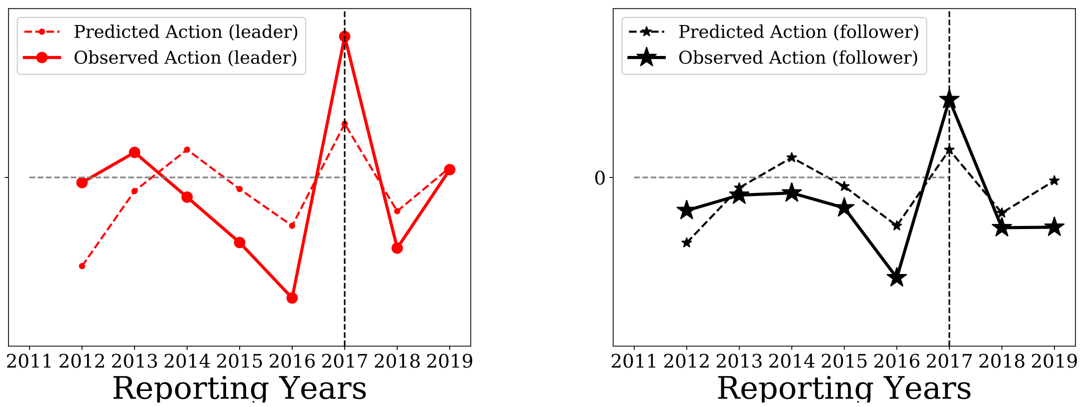
The left- and right-hand plots in Figure 2.9 show, respectively, predicted and realized actions for the leader (plan-reporting) and follower (non-plan reporting) firms for each reporting year in the dataset. The vertical dashed line in the figures indicates the beginning of the out-of-sample forecasting period. The model does a reasonable job of capturing the realized drop in emissions reduction predicted by the downward revision in beliefs following the pull-back announcement for both leader and follower firms, and correctly predicts a larger response for the leader firm. The model is also able to capture the increase in emissions reduction observed in the final year of reported data, which once again is more pronounced for leader than follower firms in the data. Overall, the out-of-sample exercise helps to increase confidence in the augmented two-firm model's ability to capture the dynamics of reported emissions abatement, given beliefs.

2.7 Conclusions

In this study, we pursue a bottom up approach to identify the determinants of firms' decision making when faced with climate regulation risk. We begin by bringing new empirical observations to the table, using firms' disclosures to the Carbon Disclosure Project (CDP), which we verify using third-party sources (Bloomberg, Thomson Reuters, and MSCI) who produce ESG ratings of firms. We document patterns in firms' beliefs about the climate regulation risks that they face, their plans for future abatement, and their actions to date on mitigating carbon emissions. We find that

Figure 2.9 *Out-of-sample Prediction*

The left plot compares the model-implied and observed abatement actions for the leader firm against reporting years in CDP. The right plot compares the model-implied and observed actions for the follower firm against reporting years in CDP. Thick (dashed) lines refer to observed (model-implied) moments. Model parameters are reported in the second column of Table 2.2..



in the five years prior to the Paris announcement, both firms' actions on carbon abatement and their beliefs about climate regulation gradually reduce. However, firms' actions and beliefs both adjust sharply around the announcement of the Paris climate change agreement in 2016, with the size of these responses depending on whether or not firms pre-announce plans for carbon emissions reduction.

To learn more about the underlying structure that can jointly rationalize these findings, we build two dynamic models of emissions abatement. The first model features an atomistic firm operating with polluting capital, which is exposed to a future climate regulation event of known intensity. To abate emissions, the firm must incur convex capital adjustment costs. We calibrate the model to the data, feeding it with the dynamics of reported beliefs, and comparing the predicted plans and actions from the model with those in the data. While the model can fit the dynamics of abatement prior to the Paris agreement, the reactions to the Paris agreement predicted by this atomistic firm model cannot match the sharp variations observed in the data.

We therefore move to a more complex model, introducing a second firm into the economy, with the goal of understanding whether the amplification we observe in the data can be rationalized by firms strategic responses to one another. Specifically, we introduce a reputation externality in the firms' payoffs, which reduces the profits of a given firm when the other firm abates, and vice-versa. We also introduce an asymmetry in firms' information about the regulation event, with the "leader" firm receiving an informative signal which is learnt by the follower. The leader moves first in the game, and the resulting equilibrium of the model predicts abatement dynamics that more closely match the patterns that we observe in the data, and are well able to capture the patterns observed in abatement following the announcement of the U.S. pullback from the Paris agreement in an out-of-sample test.

There is much work to be done on the economics of climate change and carbon emissions. Our study contributes to this important agenda by demonstrating that i) climate regulation matters greatly to firms, and ii) to better understand firms' responses to regulation events, it is important to take strategic interactions and information asymmetries between firms into account. We believe that further work to learn more about the specific microeconomic mechanisms at work along these lines will pay rich dividends.

Chapter 3

Mitigating Carbon Leakage Risk Under Imperfect Information[1]

3.1 Introduction

Climate change is caused by anthropogenic emissions of greenhouse gases (GHG) such as carbon dioxide (CO_2) and is expected to have severe ecological and economic consequences (IPCC, on Climate Change [2018]). In principle, the climate change externality should be ideally corrected by a unique global *carbon price* that covers all countries and sectors[2], yet only a few domestic climate policies have been implemented around the world so far. This has been largely attributed to the free-riding nature of climate policies, in that any jurisdiction faces weak incentives to reduce emissions when it can benefit from the reductions of others.[3]

When the regulatory framework is heterogeneous and incomplete, unilateral carbon pricing policies are at risk of undermining competitiveness of global markets inducing relocation of emissions intensive processes from regulated to deregulated countries – the so-called *carbon-leakage effect*.[4] Inefficient relocation of economic activity is one of the biggest threats to climate policymaking

[1] This chapter is an extract of a self-authored working paper *Mitigating Carbon Leakage Risk Under Imperfect Information: Evidence from the United Kingdom*, 2021.

[2] Following the logic in Pigou [1920] and Montgomery [1972], this price should equate the social cost of carbon (SCC), that is the present discounted monetary value of the global damages from an additional unit of GHG emissions, to provide the correct incentives to internalize the externality.

[3] In addition to this, it is also worth mentioning that there is currently a high degree of uncertainty and disagreement over the right value of the SCC and its practical usefulness (see the debate in Pindyck [2013] and Aldy, Kotchen, Stavins, and Stock [2021]).

[4] Carbon leakage is a broad term that encompasses the set of inefficient outcomes generated by incomplete regulation, including changes in trade flows, terms of trade, carbon emissions flows, and domestic economic indicators related to competitiveness losses like employment, production, or market share.

worldwide and at the centre of the debate about corrective designs of unilateral carbon pricing policies. This study contributes to the debate by quantifying the cost-effectiveness of a combined carbon tax - carbon subsidies scheme aimed at reducing the environmental externality while mitigating carbon leakage risk.

Over the last couple of decades, pollution subsidies have been a popular alternative to *carbon border tariffs*[5] – ideally more correct policy tools, yet practically controversial as perceived as indirect measures of protectionism incompatible with the World Trade Organization (WTO).[6] Despite the longstanding use of the pollution subsidies-approach in major carbon pricing policies such as the European Emissions Trading System (EU ETS), such approach has yet remained of a simple design in that allocation rules are currently based on "one size fits all" principles that disregard of firm-specific emissions abatement costs and other primitives of leakage propensities. Unfortunately, these simple allocation rules rank emissions intensive sectors as the most exposed to carbon leakage risk, with the result that polluting firms have been historically overcompensated by unilateral carbon pricing policies.[7] By mapping a theoretical model into a realized climate regulation in the United Kingdom, in this study I quantify the costs of allocating pollution subsidies for compliance with a carbon tax policy under a poorly refined information set, showing that counterfactual cost-efficient subsidies that take count of firm-specific leakage incentives reduce exit from the scheme risk while avoiding overcompensation of emissions intensive industries.

The first section introduces the welfare problem of a domestic regulator that wishes to impose a carbon tax while avoiding exit of the regulated firms from the domestic economy. Carbon leakage is modelled as the firm's decision to relocate its polluting processes to a foreign jurisdiction where carbon is not priced. The decision generates a twofold loss, meaning a global environmental loss related to an increase in the total stock of carbon emissions, and a domestic economic loss related to a decrease in domestic production. The regulator can control leakage by subsidising the polluting firm through an ex-post compensation for compliance with the tax. The ex-post compensation is specified in terms of a financial reward for the performance against an emission reduction target. Specifically, the firm gets compensated for the "social damage avoided" by the emissions reduction in excess of a certain target. The target is therefore the state variable that

[5]The carbon adjustment tariff applies a tax to – or requires the equivalent purchase of carbon emission allowances from – *deregulated* firms that enter a market with a certain carbon cost.

[6]See the discussion in Wooders and Cosbey [2010].

[7]See, for example, the discussion in *https://www.euractiv.com/section/energy-environment/opinion/eu-climate-targets-are-undermined-by-ets-subsidies-they-must-end/*.

controls the stock of pollution that the firm produces at zero cost, with a higher target meaning less compensation for the firm.

As a common approach in the theoretical literature on carbon leakage (see, for example, Baylis, Fullerton, and Karney [2013]), I take the social cost of carbon as known and I assume that the domestic economy is small enough so that carbon taxes and targets do not affect equilibrium prices in the product market. These assumptions allow me to express domestic welfare losses as the sum of carbon emissions stocks and value-weighted relocation propensities of domestic firms. The regulator's tradeoff comes from a binding government budget constraint which represents the opportunity cost of subsidizing pollution instead of financing (for example) green investments with higher social returns. Put differently, in the model the regulator cannot afford to prevent exit of all firms while ensuring a positive degree of emissions reduction. In a perfect setting where firms cannot exit the regulation (e.g. with infinitely high relocation costs), I show that the unconstrained optimal welfare can be achieved by setting the carbon tax at the social cost of carbon while setting all targets at 100 percentage emissions reduction. On the other hand, if firms have the opportunity to relocate, I show that the constrained optimal welfare can be achieved by the same carbon tax when targets are set so that to equalize value-weighted marginal relocation propensities across firms, therefore reconciling the baseline result outlined in Martin et al. [2014b] in the context of cap and trade markets.

The main implication of the theoretical exercise is that carbon leakage makes cost-efficient policy-making heavily reliant on the regulator's information set. Specifically, while unconstrained optimal policymaking in absence of relocation "only" requires the regulator's knowledge of the marginal social damage associated with carbon emissions, in presence of relocation risk the regulator needs to know how relocation incentives vary across firms. As a result, the less refined is the regulator's information set regarding firm-specific relocation propensities, the larger is the expected welfare loss associated with the unilateral carbon policy. To quantify such loss, I follow a procedure outlined in Jacobsen, Knittel, Sallee, and Van Benthem [2020] and approximate it as a weighted sum of the squared distances between the cost-efficient targets and the schedule of constraint-feasible targets that are imperfectly allocated in the policy.

In the remainder of the theoretical section, I specify the firm's operating profits and then determine cost-efficient targets and approximated welfare in closed form. I make a simplifying assumption in that I take optimal output choices as independent of the firm's emissions abatement choices. This amounts to assuming that adjustment effects in output growth induced by the carbon tax regulation have a negligible impact on the firm's overall cost of compliance with the regulation, and hence do not affect the firm's relocation incentives.[8] Carbon emissions enter the firm's operating costs through consumption of fossil-fuel input, and reducing fossil-fuel input costs (hence emissions) entails an adjustment cost term which models the switch to a clean technology. The adjustment cost term may vary with the firm's historical emissions and also depends on a private variable denoting the firm's type, which can for instance be conceptualized as the private quality of the clean technology. Exit has a fixed cost which is observed after the allocation of the targets, meaning that the firm decides to exit whenever the optimal compliance costs with the policy (that is, the abatement costs net of the fossil-fuel savings and the performance reward against the target) are higher than the fixed cost for exit. The choice can be conveniently expressed as a binary event which occurs when the assigned target falls above an exit threshold. The exit threshold is the sum of a predictable and an uncertain component, where the predictable component varies with the firm's ability to reduce emissions in response to an increased price of carbon and with its fixed cost of relocation.

I show that cost-efficient targets equate the predictable component of the firm's exit threshold net of a discount term which increases in the firm's contribution to welfare (e.g. how much a firm's exit is worth relative to others) and decreases in the shadow price of the budget constraint. A first prediction of the model is that, if the regulator disregards of the firm's emissions abatement incentives that feed into the predictable exit threshold, targets are necessarily skewed to favour emissions intensive firms. A second prediction is that, given that the firm's private type is perceived as an additional source of uncertainty in the firm's exit choice, cost-efficient targets vary less than what they should to minimize the constrained welfare problem. Plugging the explicit targets into the approximated welfare loss, I then determine an explicit expression to quantify the economic significance of introducing the firm's private type in the regulator's information set. As expected, the economic significance increases with the predictive power of the firm's private type on its relocation propensity, as well as with the shadow price of the budget constraint. In the remainder of the chapter, I use the model-implied predictions to assess the cost-effectiveness of a

[8] In an extended version of this chapter, I endogenize output choices and I show with a model calibration on the UK climate policy that the assumption is valid and relies on the fact that the UK carbon tax is relatively low compared with the overall cost of carbon implied by the fossil-fuel energy. Consistently with my analysis, recent empirical works on the UK and other realized carbon tax policies show that, set at the levels observed in the market, carbon taxes have a negligible impact on production (see Martin, De Preux, and Wagner [2014a] and Metcalf and Stock [2020]).

combined carbon tax-carbon subsidies scheme implemented in the United Kingdom.

Data are from energy-intensive, UK industrial firms that participate in the Climate Change Agreements (CCAs), a voluntary compensation scheme that grants large discounts on a mandatory carbon tax – the Climate Change Levy (CCL) – in exchange for compliance with emissions reduction targets. The CCAs serve the dual purpose of mitigating leakage risk associated with the CCL regulation while also ensuring (roughly) the equivalent amount of carbon savings generated by the CCL. In practice, CCAs allow participating firms to pay a diluted CCL if they comply with an emissions reduction target.[9] Compliance against the target is verified on a bi-annual basis and can be achieved either physically by reducing emissions, or financially by purchasing carbon permits to offset the emissions reduction in deficit of the target. Critically, carbon permits are bankable in that the firm receives carbon credits for excess emissions reduction that can be used to claim the CCL discount in the next bi-annual target period. Thus, reducing emissions below the target carries a marginal benefit equal to the price of the carbon permit, whereas increasing emissions carries a marginal opportunity cost equal to the discounted price of the carbon credit. As a consequence, firms' intensive margin (e.g. carbon abatement) decisions are roughly independent of the assigned target and only respond to the carbon price incentive induced by the permit price. Importantly, the permit price is fixed in CCAs, set exogenously by the regulator to match the CCL-price discount, so that carbon price incentives are roughly the same across the two regulations. Hence, is a simplified two period setting, the design of the CCL-CCAs package is well approximated by the carbon pricing scheme outlined in the theoretical section. However, an important difference with respect to the theoretical framework (which motivates the empirical section) is that targets in CCAs are allocated at the industry group-level, meaning that each firm participating in CCAs inherits the emission reduction target established in its industry group.[10]

I focus on the start of second legislation period of the CCL-CCAs regulation in 2013, which was originally meant to last until 2023 and then extended through 2025, in correspondence of which the UK government applied a series of revisions to its climate action plan that resulted in an overall (both direct and implied) increase in the price of carbon for regulated firms. I take advantage of the structural change in the UK regulatory environment to study firms' exit from the CCAs in

[9] The diluted levy is roughly 20% of the full rate, varying across fossil-fuel energy sources subject to the CCL.

[10] The Department of Energy and Climate Change (DECC) decided the targets after negotiations between the DECC and appointed representatives of the industry group associations. See further information at *https://data.gov.uk/dataset/f98a442f-32c8-4c0a-8c1e-e0576b283b89/climate-change-agreements-sector-performance-data*.

response to the newly assigned targets. Specifically, I focus on the subset of firms that migrated from the first legislation, tracking their performance in the first bi-annual target period following the start of the second legislation, between 2013 and 2015. I match regulatory compliance and emissions data in CCAs with financial and accounting data from the Bureau Van Dick (BvD) database. For robustness and descriptive purposes, I also use the *Annual Business Survey Database* (ABS), a detailed plant-level annual survey applied to a representative sample of manufacturing firms in the United Kingdom providing sensible information such as energy expenditures and CCL payments to the UK Government.[11]

Summary statistics show that firms in CCAs are on average larger, more trade intensive, and more emissions intensive than the representative set of manufacturing firms exposed to the CCL regulation. Simple back of the envelope calculations reveal that back in 2013, complying with the combined CCL-CCAs regulation was much cheaper than paying the full CCL rate, indeed, carbon subsidies in the form of target allocations accounted for roughly 50% of the total CCL revenues in the same target period, as reported by the Department of Business, Energy & Industrial Strategy (BEIS). Nonetheless, I show that roughly one fifth of the migrated firms abandoned the CCAs before the end of the first target period, suggesting potential cost-inefficiencies in the regulatory scheme. When looking at aggregate statistics from firms' own responses in the CCAs questionnaires, I show that the observed exit from the scheme is indeed most likely to correspond to either relocation or permanent closure of the regulated facilities. While it is not possible to measure the extent to which the permanent closure or relocation of the facilities generates an increase in outsourced unregulated production – meaning that I cannot measure the degree of carbon leakage associated with exit from CCAs, I find that plant-level statistics from the ABS dataset as well as aggregate statistics from the BvD dataset are consistent with presence of *some* degree of carbon leakage in the scheme. Specifically, I find that firms that exit CCAs are those with a larger proportion of local units outside of the United Kingdom, and that in the observation period during which they exit from CCAs, those firms significantly reduce their value added to output ratio with respect to compliant firms in CCAs. Together, these statistics suggest that firms that exit CCAs increase their share of material inputs sourced through international trade.[12]

[11]Office for National Statistics. (2021) *Annual Business Survey, 2005-2018: Secure Acces. [data collection]. 14th Edition. UK Data Service. SN: 7451, http://doi.org/10.5255/UKDA-SN-7451-14.*

[12]Value added indicates the value of production net of material inputs both sourced domestically and through international trade. Value added to output ratio is a canonical proxy of the firm's trade intensity and has been recently used by a related study to detect carbon leakage in the EU ETS scheme (see Colmer, Martin, Muûls, Wagner, et al. [2020]).

I therefore make use of the model prediction to assess whether exit is the "inefficient outcome of cost-efficient allocations". Specifically, as the model predicts, cost-efficiency requires that value-weighted marginal exit propensities should be equal across firms, meaning that realized (value-weighted) exit propensities should lie on a line when plotted against targets in CCAs, with the positive regression slope reflecting the shadow price of the constraint. As I show in the empirical section, the prediction does not seem to be met in the data, which in turn motivates a search for welfare-improving variation in firms' exit propensity to determine counterfactuals cost-efficient targets. In the quantitative exercise, I estimate the predictable component of the firms' exit threshold by maximum likelihood using observed exit from CCAs. Furthermore, by means of an approximated Heckman correction strategy, I use emissions reduction performance observed in CCAs to estimate unexplained variation in exit propensity that is correlated with emissions abatement costs. The exercise allows me to compute counterfactuals cost-efficient targets under a government budget equal to the one used for the realized allocations. The exercise reveals that only including firm-level observable determinants of exit would improve welfare of roughly 7% in expectation, of which a 3% improvement is uniquely attributed to the inclusion of firms' financial constraints. On the other hand, including unobservable effects in emissions abatement introduces a further 12% gain in expected welfare. Perhaps more importantly, the exercise reveals that cost-efficient compensations vary extensively within industry and that, on average, they are *lower* for more emissions intensive industries, meaning that taking count of firm-specific carbon leakage incentives reduces overcompensation of emissions intensive firms.

3.2 Model

In this Section, I study the welfare maximization problem of a domestic regulator that aims to reduce the climate externality by imposing a carbon tax on firms that operate in the domestic economy. I take as given the existence of a well defined marginal social damage of the externality, meaning that I abstract from uncertainty surrounding the specification and measurement of the social cost of carbon.[13] Furthermore, as a common approach in the literature about unilateral carbon pricing policies, I address the basic issues arising from international emissions leakage parsimoniously using a two-country model and disregarding of general equilibrium effects of the policy. Emissions leakage is modelled as the firm's relocation choice and is deemed inefficient

[13] For the longstanding debate on the social cost of carbon and its measurement, see among others Drupp, Freeman, Groom, and Nesje [2018].

by the domestic regulator in that it generates a twofold loss in social welfare, meaning a global environmental loss related to an increase in the total stock of carbon emissions, and a domestic economic loss related to a decrease in domestic production.

3.2.1 A Domestic Carbon Tax

Consider two time periods $t = 0, 1$ and a set $i = 1, ...n$ of polluting firms operating in the domestic economy. Each firm i's emissions stocks accumulate as

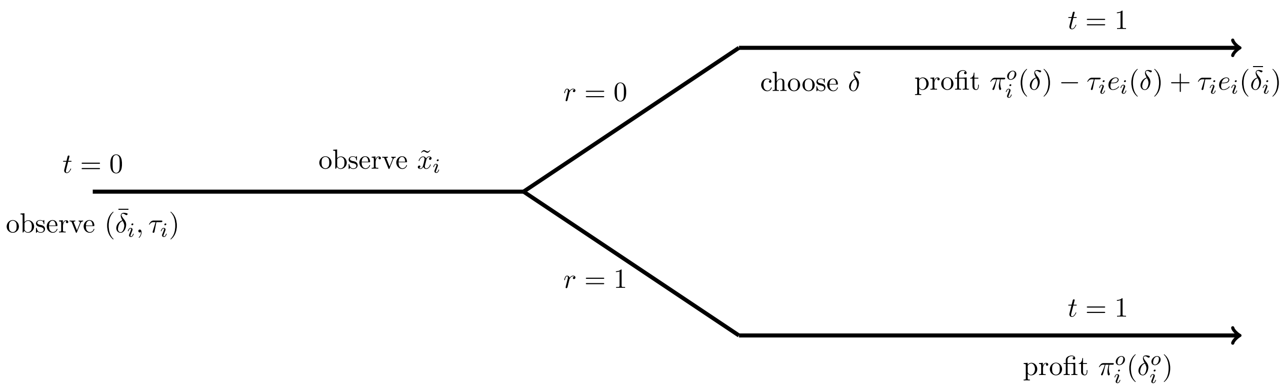
$$e_i(\delta) = e_{i0}(1 - \delta) \tag{3.1}$$

with e_{i0} firm i's historical emissions and δ a choice variable denoting the emissions abatement rate.[14] For a certain abatement rate δ, denote $\pi_i^o(\delta)$ as firm i's optimal operating cashflow

$$\pi_i^o(\delta) = \max_y \pi_i(y, \delta) \tag{3.2}$$

where y is the output choice variable, and denote δ_i^o the abatement rate that maximizes the unconstrained cashflow in (3.2).

Assume that each firm $i = 1, \ldots n$ is subject to a *carbon tax* τ_i and an *emissions abatement target* $\bar{\delta}_i$ described in detail below. The timeline of the regulated firm model then reads



In the first time period, firm i observes the schedule $(\tau_i, \bar{\delta}_i)$ implemented by the domestic regulator. At an interim date after the first time period, the firm observes a cost shock $\tilde{x}_i$ which denotes its cost of exit from the domestic economy to relocate to a foreign jurisdiction where emissions are not regulated, with $\tilde{x}_i$ distributed as $\tilde{x}_i \sim \mathcal{N}(\bar{x}_i, \sigma_x)$ with $\bar{x}_i > 0$. After observing the cost

[14] I choose this specification as it maps directly into the climate regulation implemented in the United Kingdom.

shock $\tilde{x}_i$, the firm decides whether to comply with the domestic regulation or to relocate, with the binary variable $r = \{0, 1\}$ denoting the firm's relocation choice. If the firm decides to stay, e.g. $r = 0$, it will choose an abatement rate δ that takes count of the fact that carbon emissions are taxed at τ_i. If the firm decides to exit, e.g. $r = 1$, it will choose the abatement rate δ_i^o that achieves the unconstrained maximum cashflow in (3.2). In the second time period, firm i realizes profits from operation and, if it has decided to comply with the carbon policy, it receives a transfer $\tau_i e_i(\bar{\delta}_i) = \tau_i e_{i0}(1 - \bar{\delta}_i)$ from the regulator.

Following the canonical specification in Montgomery [1972], one can define the emissions abatement cost as the difference between the unconstrained maximum cashflow $\pi_i^o(\delta_i^o)$ and its maximum when the emissions abatement rate equals δ, that is

$$C_i(\delta) = \pi_i^o(\delta_i^o) - \pi_i^o(\delta) = \max_{\delta} \pi_i^o(\delta) - \pi_i^o(\delta) \tag{3.3}$$

where clearly $C_i(\delta_i^o) = 0$, then firm i's problem can be expressed analytically as

$$\min_{r,\delta} \; (1 - r)\big(C_i(\delta) + \tau_i(e_i(\delta) - e_i(\bar{\delta}_i))\big) + r\tilde{x}_i \tag{3.4}$$

Deriving (3.4) with respect to the abatement choice δ gives

$$\frac{dC_i(\delta_i^*)}{d\delta} + \tau_i \frac{de_i(\delta_i^*)}{d\delta} = 0 \tag{3.5}$$

with δ_i^* denoting the optimal abatement choice for a given carbon tax τ_i, while the optimal relocation choice satisfies

$$r_i^*(\tau_i, \bar{\delta}_i) = 1\{\tilde{x}_i \leq C_i^*(\tau_i) + \tau_i(e_i^*(\tau_i) - e_i(\bar{\delta}_i))\} \tag{3.6}$$

where $C_i^*(\tau_i) = C_i(\delta_i^*)$ and $e_i^*(\tau_i) = e_i(\delta_i^*)$ respectively. The expression in (3.6) states that firm i relocates whenever the exit cost shock falls below the minimum cost of compliance with the regulation.[15] One immediately notes that while the tax τ_i affects both firm i's emissions abatement choice as well as its choice to relocate, the target $\bar{\delta}_i$ affects uniquely the firm's relocation choice. Specifically, a lower emissions abatement target $\bar{\delta}_i$ decreases firm i's propensity to relocate by in-

[15] Note that I am disregarding of the option to liquidate assets (e.g. stop production) in response to the unilateral carbon tax, as formally taking count of two outside options makes the model as well as the estimation that follows more difficult. I justify this assumption heuristically in the empirical section.

creasing the ex-post transfer $e_i(\bar{\delta}_i)$ without altering the original carbon price incentive τ_i. This in turn means that the regulator can virtually solve the carbon-leakage problem by "throwing money" at regulated firms in order to prevent them from relocating.[16] Clearly though, when it comes to subsidizing pollution, it is highly unrealistic to assume that the regulator has deep pockets in that there is a huge (social and political) opportunity cost of using government budget to help emissions intensive firms instead of investing in projects with positive social returns. To take count of this opportunity cost, I assume that the regulator is constrained in the aggregate amount of carbon subsidies it can use to prevent carbon leakage of regulated firms.

More formally, denoting a as the marginal social damage of carbon emissions, I specify the regulator problem as

$$\mathcal{L}^* = \min_{\{\tau_i,\bar{\delta}_i\}} \mathbb{E}\big[\sum_{i=1}^{n}(1 - r_i^*(\tau_i, \bar{\delta}_i))(C_i^*(\tau_i) + ae_i^*(\tau_i)) + r_i^*(\tau_i, \bar{\delta}_i)(ae_i^o + \tilde{x}_i^s)\big] \tag{3.7}$$

with $\mathcal{L}^*$ denoting the minimum welfare loss[17], subject to the constraint

$$\sum_{i=1}^{n} ae_i(\bar{\delta}_i) \leq D. \tag{3.8}$$

where $0 < D < \sum_{i=1}^{n} ae_i^o$ is a budget constraint which captures the opportunity cost of subsidizing polluting firms to prevent carbon leakage, whereas the term $\tilde{x}_i^s > \tilde{x}_i$ is the social cost of firm i's exit from the domestic economy.[18]

I first consider the case in which relocation is not possible, e.g. the relocation cost for each i and across all realizations $x_i = +\infty$. In such a case, I prove in the appendix F the following

Proposition 1. *If relocation is not possible, the carbon tax* $\{\tau_i = a\}_{i=1,\dots n}$ *and emissions reduction targets* $\{\bar{\delta}_i = 1\}_{i=1,\dots n}$ *achieve the unconstrained minimum in* (3.7).

[16] In particular it is sufficient that the target $\bar{\delta}_i \leq \delta_i^o$, meaning the target is lower than firm i's emissions abatement in absence of the regulation, for firm i to not relocate provided exit has some positive cost. This comes by construction given that $C(\delta_i^{\tau}{}_i) + \tau_i e_i(\delta_i^{\tau_i}) < C(\delta_i^o) + \tau_i e_i(\delta_i^o) = \tau_i e_i(\delta_i^o)$.

[17] This is a modified version of the baseline welfare problem in Montgomery [1972] that takes count of the relocation opportunity.

[18] One can interpret the social cost of exit $\tilde{x}_i^s$ as firm i's private cost of exit $\tilde{x}_i$ augmented of a fixed cost term which denotes the rent of the domestic land. The argument is that the fixed cost term does not feature in the firm's relocation choice as the latter continues to pay the same rent in the foreign unregulated jurisdiction, whereas it features in the domestic regulator's problem in the form of an income rent loss in the domestic economy.

Specifically, in absence of relocation, the regulator achieves the unconstrained optimum welfare by setting the carbon tax equal to the marginal social damage of carbon emissions and providing zero compensation to the firms. On the other hand, assume that $x_i < \infty$ for some realizations of the cost shock and for each firm i. In such a case, there is a positive relocation propensity which raises the marginal benefit of decreasing the target $\bar{\delta}_i$ and therefore subsidize pollution. I prove in the appendix the following

Proposition 2. *If relocation is possible, the carbon tax $\{\tau_i = a\}_{i=1,\ldots n}$ and emissions reduction targets $\bar{\delta}_i^*$ satisfying the Euler condition*

$$\frac{\partial \mathbb{E}[w_i(a) r_i^*(\bar{\delta}_i^*, a)]}{\partial \bar{\delta}_i} = \lambda \tag{3.9}$$

with weights $w_i(a) = \frac{v_i(a)}{ae_{i0}}$ and $v_i(a) = ae_i^o + \tilde{x}_i^s - C_i^*(a) - ae_i^*(a)$ achieve the constrained minimum in (3.7).

The proposition states if relocation is possible, then the regulator achieves the constrained optimum welfare by setting the carbon tax equal to the first-best case $\tau_i = a$, while setting emissions reduction targets so that to equalize value-weighted marginal relocation propensities across firms. Proposition 2 is an extension of the theoretical result outlined in Martin et al. [2014b] in the context of a cap and trade market subject to carbon leakage. Note that the simplicity of the constrained optimum relies on the assumption that the domestic economy is small enough so that carbon taxes and targets do not affect prices in equilibrium. While this is a common assumption in the literature on carbon leakage, it is worth mentioning that it may be particularly strong as far as the impact on fossil-fuel energy prices are concerned, and particularly the impact of the regulation on the domestic price of electricity, which is usually a highly segmented market. If this assumption was relaxed, then one firm's target would affect, through its impact on the firm's exit choice and therefore on the domestic demand of electricity in equilibrium, the compliance cost of the other firms in the economy. This would in turn introduce cross-derivatives in the Euler condition (3.9) as well as a deviation from the Pigouvian benchmark $\{\tau_i = a\}_{i=1,\ldots n}$. Presumably though, throughout this equilibrium channel, aggregate compensations should be lower than the case analysed in this chapter.

An important implication is that in presence of relocation risk, cost-efficient policymaking requires a more refined information set than in the first-base case with no relocation. Specifically, while unconstrained optimal policymaking in absence of relocation "only" requires the regulator's knowledge of the marginal social damage associated with carbon emissions, in presence of relocation risk the regulator needs to know how relocation incentives vary across firms. As a result, the less refined is the regulator's information set regarding firm-specific relocation propensities, the larger is the expected welfare loss associated with the unilateral carbon policy.

Measuring firms' relocation incentives has perhaps been one of the major historical challenges in climate policymaking worldwide. To circumvent the informational asymmetries, regulators have introduced complicated lobbying schemes where firms would report expert information over compliance costs with the policy in exchange for more favourable policy conditions (this approach was adopted to a different extent both in the case of the EU ETS as well as in the climate policy studied in this chapter). However, as I argue formally in an extended version of this chapter, due to a fundamental disalignment of incentives over the firm's report, such expert lobbying schemes are likely to fail in delivering truthful reporting and/or come at additional costs for either the regulator or for the firms. In this study, as a necessary step to evaluate potential gains from the implementation of more incentive-compatible designs of unilateral carbon pricing policies, I quantify the welfare loss associated with the allocation of constraint-feasible subsidies under an imperfect information set. To do that, I follow the procedure in Jacobsen et al. [2020] and specify the welfare losses of moving away from the optimal allocations $\bar{\delta}_i^*$ in (3.9) to alternative feasible allocations $\hat{\delta}_i$ as a weighted average of the two allocations, namely $\bar{\delta}_i(b) = b\bar{\delta}_i^* + (1-b)\hat{\delta}_i$, and then I integrate the marginal welfare loss as a function of the weight b between 0 and 1. The procedure gives the following result, proved in the appendix

Proposition 3. *The welfare loss of moving away from optimal targets $\{\bar{\delta}_i^*\}_i$ in (3.9) to alternative constraint-feasible targets $\{\hat{\delta}_i\}_i$ is approximated by half of the sum of their squared distances weighted by the sensitivity of the value-weighted marginal exit propensity*

$$\mathcal{L}\big(\{\hat{\delta}_i\}_{i=1,..n}\big) - \mathcal{L}^* = \frac{1}{2}\sum_i e_{i0}\frac{\partial^2 \mathbb{E}[w_i(a)r_i^*(\bar{\delta}_i^*, a)]}{\partial \bar{\delta}_i^2}(\hat{\delta}_i - \bar{\delta}_i^*)^2 \tag{3.10}$$

3.2.2 Solving the Model

In what follows, I propose a simple specification of the firm's operating cashflow in (3.2), from which I derive optimal abatement and relocation choices, as well as cost-efficient targets.

I make a simplifying assumption in that I take optimal output choices as independent of the firm's emissions abatement rate; this amounts to assuming that adjustment effects in output growth induced by the carbon tax regulation have a negligible impact on the firm's overall cost of compliance with the regulation, and hence do not affect the firm's relocation incentives. In an extended version of this chapter, I endogenize output choices and I show that the assumption is valid provided the level of the carbon tax remains relatively low compared to the historical cost of fossil-fuel energy. In line with my analysis, related empirical work has indeed showed that historically, carbon tax policies have had a negligible impact on firm's output revenues (see Martin et al. [2014a] and Metcalf and Stock [2020]).

Denote firm i's optimal operating cashflow as

$$\pi_i^o(\delta) = py_i^o - se_{i0}(1-\delta) - \frac{1}{2}\psi_i(\delta - \theta_i)^2 \tag{3.11}$$

where the first term indicates optimal output revenues, the second term denotes the total cost of fossil-fuel input, with s the fossil-fuel implied cost of carbon, whereas the third term denotes an adjustment cost in emissions abatement, intended as the cost incurred when moving to a zero-carbon technology, where ψ_i is the adjustment cost parameter and θ_i is a private type variable denoting the firm's private opportunity to adopt the zero-carbon technology.[19]

Optimal abatement and exit

Plugging the expression for the operating profits in (3.11) into the abatement cost (3.3) and solving the Euler equation in (3.5) for δ_i^*, one gets

$$\delta_i^* = \theta_i + \frac{e_{i0}}{\psi_i}(s+a) \tag{3.12}$$

The abatement response in (3.12) increases with the levy-augmented price of carbon, $s+a$, whereas can increase or decrease in historical emissions depending on the curvature of the parameter ψ_i as

[19]The specification has an implicit assumption in that the firm can only transition from the historical polluting technology which relies on fossil-fuel energy at input price s, to a new clean technology which relies on zero-carbon energy with input price normalized to zero. This amounts to assuming that intermediate transitions such as simple switches from more emissions intensive to less emissions intensives fossil-fuel products have negligible impact on the firm's carbon emissions stock. Such an assumption is both consistent with the firms' own disclosures from the CCAs questionnaire (reported in the data appendix G), as well as with recent evidence outlined in a related paper by Colmer et al. [2020].

a function of historical emissions. Specifically the abatement rate *decreases* in historical emissions to the extent that the cost function is *convex* in emissions, it increases with emissions if the cost function is concave in emissions, whereas it is independent of emissions if the cost function is linear in emissions. Put differently, everything else equal, depending on the adjustment cost one should expect emissions intensive firms to perform better or worse than less emissions firms subject to the regulation.

The optimal relocation choice in (3.6) can be conveniently expressed as an upperbound on the target

$$\mathrm{r}_i^* = 1\{\tilde{z}_i \leq \bar{\delta}_i\} \tag{3.13}$$

where $\tilde{z}_i$ is a random exit threshold which determines firm i's propensity to relocate for a given target (e.g. the lower the exit threshold, the higher the firm's propensity to relocate for a given target), which takes the explicit expression

$$\tilde{z}_i = \underbrace{\theta_i + \frac{e_{i0}}{\psi_i}(s + \frac{1}{2}a)}_{\text{emissions abatement}} + \underbrace{\frac{\tilde{x}_i}{ae_{i0}}}_{\text{relocation}} \tag{3.14}$$

determined by substituting the optimal abatement δ_i^* into the abatement cost (3.3). As I show in detail in the appendix, the exit threshold in (3.14) is composed of two terms: the first term is the net benefit of physical compliance (e.g. emissions abatement) with the regulation, whereas the second term is the firm's sunk cost of relocation per unit of its historical cost of carbon. The expression clearly shows that disregarding of optimal adjustment effects in carbon emissions (e.g. disregarding of the first term) results in the relocation propensity being unambiguously increasing in the firm's historical emissions, whereas taking count of these effects may result in the firm's relocation propensity being non-monotonic or increasing in historical emissions, depending on the functional form of ψ_i. This observation sets the ground for the analysis that follows, anticipating that if the regulator only takes count of historical exposure to leakage disregarding of emissions adjustment effects, then targets are systematically skewed to favour emissions intensive sectors.

Cost Efficient Targets

In the remainder of the section, I specify a probability distribution for the exit shock $\tilde{x}_i$ and for the firm type θ_i and I derive a closed form expression for the cost-efficient targets satisfying (3.9). Importantly, as the type θ_i is not observed by the regulator, it is perceived as an additional source of uncertainty in the firm's relocation choice at the timing of setting of the targets. More specifically, the regulator assigns the target $\bar{\delta}_i$ that satisfies (3.9) where the firm's relocation choice is averaged across all possible realizations of the shock $\tilde{x}_i$ as well as of the type θ_i. I therefore quantify the economic significance of introducing firm i's private type θ_i in the regulator's information set by making use of the approximated expression for the expected welfare loss in (3.10).

Lemma 1. *Assume henceforth that $\theta_i \sim \mathcal{N}(0, \sigma_\theta)$ and $\tilde{x}_i \sim \mathcal{N}(\bar{x}_i, \sigma_x)$ are drawn from independent normal distributions. The exit threshold in* (3.14) *can be expressed as*

$$\tilde{z}_i = \mathbb{E}[\tilde{z}_i] + \tilde{\epsilon}_i \tag{3.15}$$

where $\mathbb{E}[\tilde{z}_i] = \frac{e_{i0}}{\psi(e_{i0})}(s + \frac{1}{2}a) + \frac{\bar{x}_i}{ae_{i0}}$ is the predictable component of the threshold, while $\tilde{\epsilon}_i \sim \mathcal{N}(0, \sigma_i)$ is a normally distributed de-meaned shock with volatility $\sigma_i = \sqrt{\sigma_\theta^2 + \sigma_x^2/(e_{i0}^2 a^2)}$

In what follows, I further assume that the social value of exit can be well approximated by the firm's historical operating capital $v_i \approx k_{i0}$,[20] which in turns means that the weight w_i is proportional to the inverse of the firm's historical emissions intensity $w_i \approx \frac{k_{i0}}{ae_{i0}}$. Under such conditions, it holds the following

Corollary 1. *Assume that the exit threshold $\tilde{z}_i \sim \mathcal{N}(\mathbb{E}[\tilde{z}_i], \sigma_i)$ is distributed as specified in Lemma 1 and that firm i's value $v_i \approx k_{i0}$. Then for each firm $i = 1, \ldots n$, cost-efficient targets as specified in Proposition 2 take the explicit expression*

$$\bar{\delta}_i^* = \mathbb{E}[\tilde{z}_i] - \sigma_i^2 \sqrt{-2log(\sqrt{2\pi}\sigma_i \frac{\lambda}{w_i})} \tag{3.16}$$

with $w_i \approx \frac{k_{i0}}{ae_{i0}}$ is the firm-specific weight and λ is the shadow price of the government budget constraint D.

The expression in (3.16) is stating that, everything else equal, cost-efficient targets should increase with firm i's predictable component of the exit threshold $\mathbb{E}[\tilde{z}_i]$ as well as increase (decrease) with the shadow price of the budget constraint λ (with firm i's contribution to social welfare w_i). Clearly, the shadow price of the constraint λ is determined in equilibrium so that total compens-

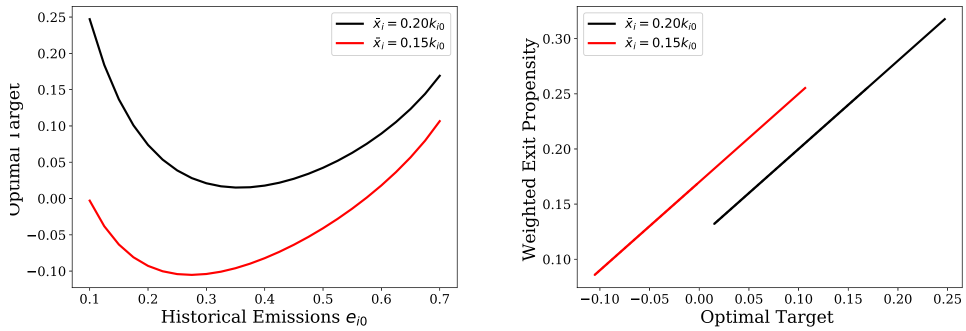
[20]This amounts to assuming that the domestic economic loss associated to the firm's exit is higher than the global damage associated with the increase in total emissions stock $\tilde{x}_i^s \approx k_{i0} >> a(e_i^o - e_i^*(a))$, which is likely to be the case for relatively small regulations such as the on in the UK.

ations equate the budget constraint and therefore depends on the cross-sectional distribution of exit thresholds.

The left and right plots in Figure 3.1 show equilibrium cost-efficient targets against historical

Figure 3.1 *Equilibrium Cost-Efficient Target and Exit Propensity*

The left plot shows equilibrium cost-efficient targets as a function of the firm's historical emissions, the right plot shows expected relocation propensities against equilibrium cost-efficient targets. Black and red lines refer to different values of the expected exit cost $\bar{x}_i$. Other model parameters are $\lambda = 0.8$, $k_{i0} = 1$, $\psi = 12$, and $\sigma_i = 0.15$.



emissions and relocation propensities against cost-efficient targets respectively. As the left plot in Figure 3.1 shows, targets have a non-monotonic relationship with respect to the firm's historical emissions in equilibrium. The plots refer to the simplified case where the emissions adjustment cost $\psi_i = \psi e_{i0}$ is linear in historical emissions, so that following the discussion in the previous section, emissions adjustment effects do not contribute to the sensitivity of the exit threshold to the firm's historical emissions. Specifically in such a case, the target varies with historical emissions only throughout the extensive margin determinants of relocation and with the firm-specific weight w_i. From the previous section, one knows that if emissions adjustment effects don't play a role in shaping the firm's relocation choice, then the exit threshold is expected to decrease in historical emissions, suggesting that the target should also decrease in accordance with the expression in (3.16). However, given that the weight w_i is also decreasing in historical emissions, and that the target decreases with the weight w_i in accordance with the expression in (3.16), then the target is also expected to increase in historical emissions. As a result, cost-efficiency requires that targets have a U-shaped relationship with respect to emissions in equilibrium. As observed from the left plot in Figure 3.1, increasing (decreasing) the expected exit cost $\bar{x}_i$ skews the U-shape in favour of more (less) emissions intensive firms respectively. Independently of historical emissions, the right plot in Figure 3.1 shows that if targets are assigned in a cost-efficient way, then weighted relocation propensities evaluated in the optimal targets should lie along a straight line whose slope is given by the shadow price of the budget constraint. This statistics is central in the empirical analysis that follows as it provides a sufficient condition to test whether the realized exit observed from the UK climate policy is the inefficient outcome of cost-efficient allocations.

To conclude, I quantify the economic significance of the private type θ_i in terms of the expected welfare loss incurred when allocating targets as in (3.16) instead of type-sensitive targets where the private type θ_i enters the predictable component of the exit threshold and the uncertainty is only related to the irreducible noise. From Proposition 3, I prove in the appendix F the following

Corollary 2. *Let conditions outlined in Corollary 1 hold. Then the economic significance of introducing the firm's private type θ_i into the regulator's information set can be quantified as*

$$\Delta\mathcal{L}^* = \frac{1}{2}\frac{\sigma_\theta^2}{\sigma_i}\sum_i \lambda e_{i0}\sqrt{-2log(\sqrt{2\pi}\sigma_i\frac{\lambda}{w_i})} \tag{3.17}$$

Notably, the expression in (3.17) is independent of the expected threshold $\mathbb{E}[\tilde{z}_i]$ and fully identified by the variances $\sigma_i^2, \sigma_\theta^2$, the historical emissions e_{i0}, the weight w_i, as well as the shadow price of the budget constraint λ.

3.3 The experiment: UK Climate Change Agreements

Data are from energy-intensive, UK industrial firms that participate in the Climate Change Agreements (CCAs). The CCAs is a scheme that grants large compensations on a mandatory carbon tax, the Climate Change Levy (CCL), in exchange for compliance with emissions reduction targets. The CCL is a tax applied to fossil-fuel energy bills of UK firms operating in the industrial, commercial, agricultural and public services sectors[21]. The CCAs scheme is voluntary and designed to subsidize a subset of sectors subject to the CCL that are targeted as vulnerable to *carbon leakage risk*, those sectors are notably identified as the ones that are trade-exposed and either highly-polluting (e.g. steel), electricity-intensive (e.g. aluminum), or both.[22] In 2013, the UK Committee on Climate Change[23] identified iron and steel, refined petroleum products, aluminium, other inorganic chemicals, pulp and paper and rubber tyres as vulnerable sectors, along with other

[21]Fossil-fuel sources include fuel oil, coal, natural gas, and electricity.
[22]See, among others, Fowlie and Reguant [2018]
[23]See $https://www.theccc.org.uk/publication/2013-progress-report/$.

energy-intensive sectors including – but not limited to – poultry meat, motor manufacturing, and textile products.

The CCAs serve the dual purpose of mitigating leakage risk associated with the CCL regulation while also ensuring (roughly) the equivalent amount of carbon savings generated by the CCL. In practice, CCAs allow participating firms to pay a diluted CCL if they comply with an emissions reduction target.[24] Compliance against the target is verified on a bi-annual basis and can be achieved either physically by reducing emissions, or financially by purchasing carbon permits to offset the emissions reduction in deficit of the target. Critically, carbon permits are bankable in that the firm receives carbon credits for excess emissions reduction that can be used to claim the CCL discount in the next bi-annual target period. Thus, reducing emissions below the target carries a marginal benefit equal to the price of the carbon permit, whereas increasing emissions carries a marginal opportunity cost equal to the discounted price of the carbon credit. As a consequence, firms' intensive margin (e.g. carbon abatement) decisions are roughly independent of the assigned target and only respond to the carbon price incentive induced by the permit price. Importantly, the permit price is fixed in CCAs, set exogenously by the regulator to match the CCL-price discount, so that carbon price incentives are rhoughly the same across the two regulations. Hence, is a simplified two period setting, the design of the CCL-CCAs package is well approximated by the carbon pricing scheme outlined in the theoretical section. However, an important difference with respect to the theoretical framework (which motivates the empirical section) is that targets in CCAs are allocated at the industry group-level, meaning that each firm participating in CCAs inherits the emission reduction target established in its industry group.[25]

3.3.1 Sample Selection

The first legislation period of the CCL-CCAs regulation started in April 2001 and terminated in March 2013, while second legislation period started in April 2013 and was originally set to expire in March 2023.[26] In correspondence of the start of the second legislation period in 2013, the UK government applied a series of revisions to its climate regulatory package that resulted in an overall (direct and implied) increase in the price of carbon for manufacturing firms operating in the United

[24]The diluted levy is roughly 20% of the full CCL rate, varying across energy sources.

[25] The Department of Energy and Climate Change (DECC) decided the targets after negotiations between the DECC and appointed representatives of the industry group associations.

[26]It was then extended throughout March 2025.

Kingdom.[27] The first important change affected directly CCAs participants in that, prior to April 2013, firms that did not meet their targets could still be eligible for the CCL discount if the target was met at the industry group level, while from April 2013 onwards, each firm would have responded for its own performance against the target. The second important change affected indirectly CCAs participants in that, starting from April 2013, a Carbon Price Support (CPS) rate was introduced for UK electricity generating firms subject to the EU Emissions Trading Scheme (EU ETS). Specifically, UK electricity firms subject to the EU ETS had to pay a time-varying rate called the CPS, which was set compensate any shortfall of the EU ETS price with respect to a domestic Carbon Price Floor (CPF) established in 2013.[28] The introduction of the CPS rate raised sensibly UK electricity prices following 2013[29] and might have otherwise affected regulatory compliance choices of energy-intensive firms subject to the CCL-CCAs regulation. I take advantage of this structural change in the UK regulatory environment to study the exit propensity of leakage-vulnerable firms participating in CCAs in response to the newly assigned emissions reduction targets (e.g. to the newly assigned pollution subsidies for compliance with the CCL). Specifically, I focus on the subset of CCAs participant firms that *migrated* from the first legislation, and track their performance in the first bi-annual target period following the start of the second legislation (that is, between 2013 and 2015).

For the analysis that follows, I therefore combine firm-level environmental data from migrated firms in CCAs with financial and production data from the Bureau van Dijk (BvD) database. For robustness and descriptive purposes, I also use the Annual Business Survey Database (ABS), a detailed plant-level annual survey applied to a representative sample of manufacturing firms in the United Kingdom providing sensible information such as energy expenditures and CCL payments to the UK Government.[30]

CCAs provides data on produced emissions and emissions reduction performance (against the

[27] In addition to the changes mentioned, the UK government also enacted more stringent mandatory emissions reporting requirements to cover all public firms operating in the United Kingdom. This regulatory change is not included in the analysis given the scarcity of public firms in the sample.

[28] The CPS rate would therefore raise whenever the EU allowance price would fall below the CPF level, so that to maintain a minimum price of carbon for electricity generated in the UK. The predetermined CPF was set to start at 9£/mtCO_2e in 2013 and reach 18£/mtCO_2e by 2015. The CPF was originally meant to raise further after 2015, however, given the continuing disappointment with the level of the EU ETS price (roughly 3.3 £/mtCO_2e between 2013 and 2015 using the yearly GBPUSD exchange rate as of 2013), the CPF level was freezed at 18£/mtCO_2e to avoid imposing further competitive disadvantages on the UK economy.

[29] See, for example, Oosterom [2020].

[30] Office for National Statistics. (2021) *Annual Business Survey, 2005-2018: Secure Acces. [data collection]. 14th Edition. UK Data Service. SN: 7451, http://doi.org/10.5255/UKDA-SN-7451-14.*

assigned target) at the target unit-level. A target unit is a facility or a set of facilities[31] owned by the firm participating in CCAs. Each target unit inherits the emission reduction target of the industry group in which is incorporated. Some large firms (approx 15% of the entire sample) enter multiple times in the dataset as their facilities are allocated to different industry groups depending on their production goods. I treat target units linked to the same firm as different observations in the dataset. However, I eliminate the firms that strategically exit the regulation in 2013 to enter industry groups with more favourable targets in the next target period[32]. This because I am interested in permanent exit from the regulation in response to the targets. Each target unit is matched to a firm in the universe of manufacturing firms in BvD by means of its UK registered number. The BvD dataset contains detailed firm-level information on financial and accounting characteristics. For the purpose of the analysis, I collect value added, turnover, total assets, and credit limit of the firms between 2012 and 2016, covering the entire target period 2013–2015 in CCAs. I require that firms report at least their assets in 2012. Furthermore, I also require that each industry group is composed of at least 5 target units. The final sample has a total of 2,232 target units owned by 1,961 unique firms in a total of 37 industry groups.

The ABS dataset is a detailed plant-level annual survey applied to a representative sample of roughly 50,000 manufacturing firms in the United Kingdom, providing sensible information such as energy expenditures and CCL payments to the UK Government. Over the survey period 2012–2016, the ABS panel covers slighlty more than 50% of the merged CCAs/BvD dataset, with little variation of the matched sample across years. The relatively poor coverage of the dataset limits its use in the estimation exercise that follows. The dataset is yet included in this descriptive section as it allows for a comparison between CCAs firms and a representative sample of manufacturing firms subject to the full CLL, providing insights about the external validity of the analysis.

3.3.2 Empirical Evidence

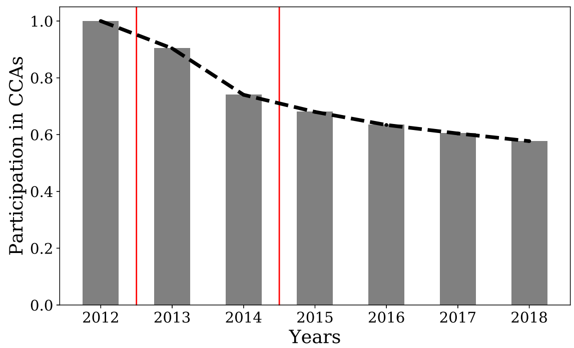
Figure 3.2 shows, across each observation year since the start of the second CCAs legislation, the percentage of CCAs firms in the sample that continue to participate in the following years. The first striking evidence that motivates the analysis that follows is that as observed from Figure 3.2, there is indeed a pronounced exit right after the start of the second legislation, with roughly 24% of the firms in the sample abandoning the scheme during the first bi-annual target period between

[31]Over 90% of the unit agreements were linked to a single facility, while the remainder of unit agreements were linked, on average, to three facilities.

[32]I find that 8% of the firms in the migrated sample opt for this "strategic" exit.

Figure 3.2 *Participation of migrated firms across second legislation years*

The graph shows, across observation years in the dataset, the percentage of firms that migrated from the first legislation of CCAs and continue to participate in the second legislation of the CCAs.



2013 and 2015.

Table 3.1. compares the CCAs/BvD dataset with the representative universe of UK manufacturing firms subject to the CCL, as selected from ABS. Table 3.1. reports summary statistics, as of 2012, of a small set of characteristics from the combined CCAs/BvD/ABS dataset. The left column (CCAs) refers to the selected sample of firms within CCAs. The right column (universe under CCL) is the representative set of firms manufacturing firms in BSD which report strictly positive CLL expenditures in 2012. As described by the total number of employees, total assets, and turnover, firms participating in CCAs are on average three times larger than the universe of firms subject to the CCL. In the appendix G, I list the top twenty firms by total assets participating in CCAs: among those firms, there are top players such as the Tata Steel UK and Shell UK corporations for the steel and energy sectors, the Jaguar and Ford motor companies for the motor manufacturing sector, the Tesco, WM Morrison, and Sainsbury's supermarkets for the wholesale retail food sector, as well as the BAE Systems and Astrazeneca corporations for the aerospace defence and chemical pharmaceutical sectors respectively. Collectively, in the last target period preceding the start of the second legislation, CCAs firms reported 19 mtCO_2e of aggregate carbon emissions generated by combustion of fossil-fuel, accounting for roughly 30% of the combined industrial and agricultural emissions as reported by the Department of Business, Energy & Industrial Strategy (BEIS).

Firms participating in CCAs are, on average, slighlty more energy intensive than the universe of

Table 3.1. *Summary Statistics*

Data are from the CCAs/BvD/ABS dataset. The left column (CCAs) refers to the selected sample of firms within CCAs. The right column (universe under CCL) is the representative set of firms manufacturing firms which report CLL expenditures at least in 2012. Number of Employees, Total Assets, Turnover, and Credit Line to Turnover Ratio are from the BvD database. Emissions covered are from the CCAs dataset. The remainder of variables are from the ABS dataset. All continuous variables are winsorized between the 5^{st} and the 95^{th} percentiles of the pooled distribution.

	CCAs		Universe under CCL	
Variable	**Mean**	**(Std.)**	**Mean**	**(Std.)**
Number of Employees	1,143.5	(1,993.1)	239.8	(1,179.9)
Total Assets(£ml)	128.5	(292.5)	50.6	(200.5)
Turnover (£ml)	150.0	(182.9)	46.7	(114.2)
Purchased Energy (£ml)	4.43	(3.79)	0.90	(2.26)
Credit Limit (£ml)	3.87	(10.6)	1.68	(1.02)
Energy to Turnover Ratio	0.04	(0.04)	0.03	(0.04)
Credit Line to Turnover Ratio	0.04	(0.03)	0.04	(0.03)
Value Added to Turnover Ratio	0.35	(0.29)	0.52	(0.43)
Emissions Covered in CCAs (ktCO_2e)	11.5	(28.1)		
Ultimate Owner is Foreign	0.23	(0.42)	0.24	(0.43)
Unique Firms	1,961		7,332	

firms subject to the CCL, as summarized by the ratio of total energy expenditures divided by turnover. In the data appendix G I plot the conditional distribution of energy intensity across CCAs and non-CCAs participants subject to the CCL. The plot reveals a visible difference in skewness across the two distributions, with the majority of energy purchases of non-CCAs firms accounting for less than 1% of their total output. Notably, firms in CCAs also display a significantly lower value added to turnover ratio than the universe of firms subject to the CCL. This variable is used in the literature as a proxy of the firm's exposure to trade, measuring the firm's total revenues net of total material inputs, including both material inputs sourced domestically and throughout international trade (see, for example, Colmer et al. [2020]). The plot in the appendix G reveals a difference in the distribution of CCAs and non-CCAs participants along the trade intensity dimension. These differences are consistent with the fact that firms eligible to participate in CCAs are – by definition of leakage-vulnerable firms – either energy intensive, or trade intensive, or a combination of the two.[33]

[33] Moreover, within eligible sectors, eligible firms should own facilities classified as energy intensives by the DECC (see more information at *www.gov.uk*).

It is interesting to note that, on average, CCAs firms spend in energy an amount which overpasses their credit limit. The variable credit limit is available from BvD and refers to the amount of flexible (e.g. immediate) credit a financial institution can extend to a firm, which can be intended as a metric of the firm's liquidity/internal finance. Therefore, to the extent that the cost of external finance is higher than the cost of internal finance, an increase in the CCL which pushes the firm's energy expenditures further beyond its credit limit could increase considerably the firm's cost of compliance with the regulation. To measure the cost of carbon implied by the CCL and compare it with the carbon permit price in CCAs, I need to convert the CCL rates from £/kWh to £/mtCO_2e. For that I need fossil-fuel to CO_2 equivalent conversion factors across the fossil-fuel sources covered by the CCL, as well as energy consumption data of UK manufacturing firms at the fossil-fuel source level. For the conversion factors, I take as a reference the estimates provided by BEIS, relative to 2012. For determining the typical fossil-fuel energy mix consumed by manufacturing firms in UK, I use data in the Quarterly Fuel Inquiry (QFI) database,[34] a quarterly panel survey directed to a representative set of energy-intensive industrial consumers, containing information about purchased volume and value of gas, electricity, gasoil, coal, and heavy fuel oil.[35]

I estimate an average CCL-implied price of carbon of 14.9 £/mtCO_2e, varying between 12.4 and 16.5 across 2-digit sectors in the dataset. This figure represents roughly 7% of the average price of carbon implied by the typical fossil-fuel energy mix consumed by UK manufacturing firms. Within CCAs however, compliant firms would pay only 2.9£/mtCO_2e of the CCL on average, as they could claim the 12£/mtCO_2e discount if they complied (physically or financially) with the emissions reduction target. As anticipated in the introductory section, the cost of the permit was set *exactly* at 12£/mtCO_2e for the first two target periods in CCAs, and then raised to 14£/mtCO_2e in 2016. Therefore, the compensation scheme was set to reduce the burden of the regulatory policy on the extensive margin, while ensuring (on average) the same carbon price incentive to reduce emissions.

Target allocations and realized exit

Recalling the theoretical model, if all targets were set at the highest level (e.g. all emissions reduction targets equal to 100% reduction of historical emissions), then the corrective scheme would be

[34] Department of Energy and Climate Change. (2016). *Quarterly Fuels Inquiry, 1998-2015: Secure Access. [data collection]. 3rd Edition.* UK Data Service. SN: 6898, http://doi.org/10.5255/UKDA-SN-6898-3.

[35] Information about the estimation procedure is reported in the appendix G. However, access to energy consumption data from QFI is restricted and therefore QFI statistics are not reported in the appendix G.

simply equivalent to the original carbon tax, meaning that each firm's cost of compliance within CCAs would be the same as the cost of compliance with the CCL.[36] However, as the left-hand plot in Figure 3.3 reveals, targets were well below 100% and varying across industry groups in CCAs (in fact averaging around 5% emissions reduction in the target period 2013–2015), meaning that compliance with CCAs was cheaper than compliance with the CCL, and cheaper for some industry sectors than others. Specifically, the left-hand plot in Figure 3.3 shows industry-level targets relative to the target period 2013–2015 against average emissions levels of the industry group.[37] The plot shows a clear negative correlation between targets and average emissions levels of the industry group, meaning that sectors producing more emissions tend to receive proportionally higher compensations than less emissions intensive sectors. This seems partly at odds with predictions outlined in the theoretical section, in that cost-efficient targets should be U-shaped with respect to emissions, although the skewness of the shape could vary depending on emissions abatement costs, budget constraints, and potential determinants of relocation correlated with emissions. In this regard, one must note that there seems to be a significant negative correlation between emissions and import trade tariffs, reported in the appendix G, where import tariffs can be though of as affecting the domestic firm's relocation costs in the model. Consistently with recent evidence on the subject[38], this statistics suggests that carbon leakage of emissions intensive sectors is indirectly enhanced by their trade policy and, as a result, emissions intensive industries may efficiently receive lower targets than other CCAs participants.

Exit from CCAs is the primary outcome of interest in the analysis. The right-hand plot in Figure 3.3 shows the industry-level exit rate between 2013 and 2015 against assigned targets, where the exit event is a dummy variable equal to 1 in the case where the firm's target unit does not appear in the second target period of CCAs, meaning that the firm's facilities associated to that target unit are no longer regulated by CCAs after 2015. As anticipated from the plot in 3.2, roughly 24% of the migrated firms exit in the first target period, interestingly though, exit

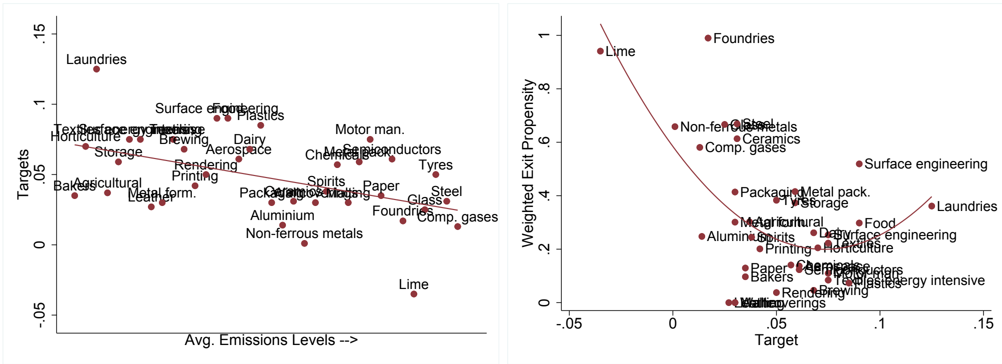
[36] Using historical emissions levels reported in CCAs, I construct in the appendix G the cumulative counterfactual distribution of the firms' compliance costs under the full CCL and the compliance costs if CCAs' targets were set at 100%, showing that the two are indeed roughly equivalent.

[37] Emissions reduction targets are expressed in terms of percentage reduction in the historical emissions of the firm. The baseline year would typically be 2009 but varying across industry groups, furthermore, some of the targets were expressed in percentage reduction of the firm's baseline emissions intensity, defined as the historical emissions produced per unit of output, instead of the firm's historical emissions.

[38] A recent work by Shapiro [2020] argues that such negative correlation is an endogenous outcome of an equilibrium model with upstream/downstream industries and lobbying for tariffs. According to the study, upstream industries - which are more emission intensive – are less protected from international import (e.g. receive lower import tariffs) because downstream industries are successfully lobbying for low tariffs on their inputs.

Figure 3.3 *Pollution Subsidies and Realized Exit*

The left plot shows emissions reduction targets relative to the first target period of the second CCAs legislation against average industry-group emissions covered in the agreement. The right plot shows weighted average exit against industry-group targets relative to the first target period of the second CCAs. Weights are computed as the emissions intensity share of the firm in the industry group.



rates vary considerably across industry groups. A central result of the theoretical analysis is that cost-efficient targets should be assigned so that to equalize (value-weighted) marginal relocation propensities across firms. If this was the case for the CCAs regulation, realized (value-weighted) exit propensities should lie on a line when plotted against targets, with the positive regression slope reflecting the shadow price of the budget constraint. However, the right-hand plot in Figure 3.3 shows that this is poorly the case for equally weighted relocation propensities. Specifically, realized exit propensities do not lie on a line but are rather U-shaped as a function of the targets: while measurement errors could play a role in explaining such observed pattern, the evidence motivates the search for welfare-improving, firm-specific counterfactual targets that could capture residual variation in exit propensities. Before proceeding with the counterfactual exercise though, it is necessary to ensure that exit from the CCAs can indeed be interpreted as a carbon leakage outcome and for that considered inefficient for the regulator. In the attempt to do that, I outline the robustness analysis that follows.

Robustness

First of all, it is worth noting that if a firm decides to exclude facilities from CCAs, then it does not necessarily mean that those facilities stop being operating. Specifically, firms might just decide to keep operating outside of the CCAs regulation, therefore paying the full rate of the CCL. However, as back of the envelope calculations have revealed, complying with the baseline CCL regulation was unambiguously more costly than complying with the targets in CCAs. This in turn suggests that when a firm removes a facility (or a set of facilities) from the CCAs, it is most likely to close that facility and possibly outsource/relocate production operations outside of the regulated jurisdiction. Unfortunately, I cannot keep track of firms' operations at the facility level, meaning that I cannot perfectly identify the nature of each firm's exit from CCAs. However, I attempt to validate the statement in two ways. First, for each enterprise owner of the target units in CCAs, I use plant-level data from the ABS database to collect information about their birth date, death date (if any), foreign ownership, and total number of operating local units. A local units in ABS is a place of work factory, a shop, or a branch of the enterprise located in the United Kingdom. It is defined as the smallest combination of legal units that has a certain degree of autonomy within an enterprise group. In such a setting, a facility subject to the CCAs is either corresponding to an entire local unit or to a portion of the local unit, in case the latter carries out industrial processes not included in the agreement. Statistics from ABS show that enterprise owners that abandoned the CCAs had on average *more* local units than compliant owners, they were *more* likely to have local units outside of the UK, and crucially they were *more* likely to close their UK local units between 2012 and 2016.[39] Second, I look directly at CCAs participants' responses from a detailed questionnaire relative to the second legislation of the CCAs. In the questionnaire, carried out at the termination of the third target period, existing or former CCAs participants are directly asked to report whether they permanently closed or relocated the facilities subject to the CCAs . As reported in the appendix G, roughly 15% of the 380 respondent firms stated that the exit from the agreement corresponded to either a permanent closure or to a relocation of the facility.[40] To the extent that this proportion is higher in the unconditional sample (e.g. also including firms that did not respond to the questionnaire), this evidence is indeed suggesting that one facility's exit from the CCAs is likely to coincide with its relocation or permanent closure.

Having determined that the exit event is associated with a decrease in regulated production, it remains to understand whether such event is effectively a bad outcome for the regulator. In the model, exit is always inefficient in that it is identified with the firm's choice to transfer production to an unregulated jurisdiction, which generates a twofold welfare loss in the domestic economy. In reality, one firm's decrease in domestic regulated production might not necessarily be offset by an increase in its own or other firms' unregulated foreign production, meaning that the firm might just decide to close the energy-intensive facility if the cumulative discounted costs from its operation

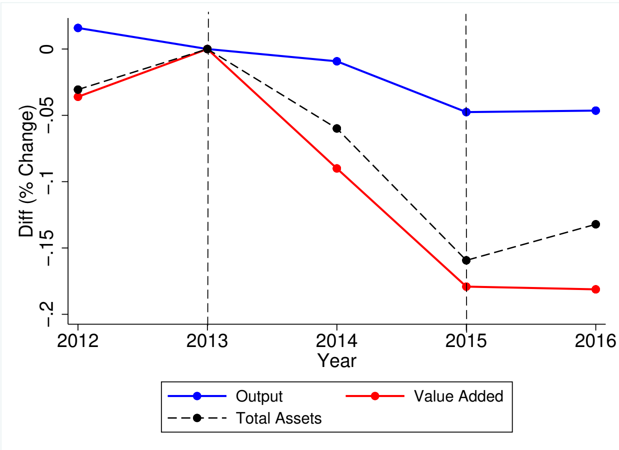
[39] Those statistics are of restricted access and therefore not reported in the appendix G.

[40] Notably, both the total exit rate as well as the relocation rate were higher for firms in energy intensive industries, despite the fact that those firms received lower targets on average.

outweighs the benefits. In such a case, it is not trivial to understand whether or not the firm's optimal termination of the facility is inefficient for the regulator as, for example, economic losses deriving from such closure might be more than offset by the social gains in emissions reduction. Luckily enough, the model offers a necessary condition to assess whether the firm's exit might have generated a certain degree of carbon leakage. Specifically as the model predicts, when leakage

Figure 3.4 *Exit*

The plot shows the difference, across compliant and non compliant firms in the dataset, in average cumulative percentage changes in output (blue line), value added (red line), and total assets (black dashed line) since the start of the second CCAs legislation in 2013. Negative values indicate that on average, non-compliant firms have decreased their historical levels of output, value added, and total assets relative to compliant firms in CCAs. Firms that have multiple target units and only a portion of them is non-compliant are treated as compliant.



happens, the firm outsources production outside of the regulated jurisdiction but continue to sell output in the market. Hence, if leakage happens then necessarily one should see that the firm's value added *drops* relative to the dynamics of its output. To the extent that exit from the CCAs has generated a certain degree of carbon leakage, one should therefore see a difference between the output to value added dynamics across compliant and non-compliant firms in CCAs. Figure 3.4 shows that this is exactly the case. The plot shows the difference, across compliant and non compliant firms in the dataset, in average cumulative percentage changes in output (blue line), value added (red line), and total assets (black dashed line) since the start of the second CCAs legislation in 2013. As observed, there is a clear divergence in the relative dynamics of output and value added across the two group of firms, in that while non-compliant firms decrease output revenues roughly 5% more than compliant firms, they decrease value added roughly 17% more than compliant firms between 2013 and 2016. That is according to the graph, during the observation period in which CCAs firms have abandoned the scheme, those firms have necessarily increased their share of outsourced material inputs relative to firms that complied with the scheme. Assuming that the outsourced production would come from unregulated (or less regulated) jurisdictions, exit from the CCAs could therefore have generated leakage for up to 12% of regulated production with respect to 2013 levels.

3.3.3 Counterfactual Targets

In this section I perform a quantitative exercise to derive counterfactuals cost-efficient targets and estimate the welfare losses associated with the imperfect allocation of pollution subsidies across firms. First, I use observed exit from the CCAs scheme to estimate firm-level exit thresholds. Then, by means of an approximated Heckman correction strategy, I use observed emissions abatement performance in CCAs to retrieve the residual variation in observed exit that is correlated with unobserved determinants of emissions abatement (that is, the unobserved component of the exit threshold correlated with emissions abatement costs). Therefore, I plug the estimated quantities into the explicit expression for the cost-efficient targets in (3.16), where the shadow price λ is determine so that aggregate subsidies match the actual budget allocated for the policy, while the weights w_i are set equal to the inverse of the firm's emissions intensity. Importantly, by differentiating across observed and unobserved determinants of exit, the exercise sheds light on the relative importance of private to public information in emissions abatement and whether alternative designs that take count of informational asymmetries should be practically considered in unilateral carbon pricing policies.

Linear regressions

Before proceeding with the quantitative exercise, I report in Table 3.2. linear regressions of firm-level performance and exit in CCAs against a selected set of characteristics. The performance variable is a dummy indicator equal to one (zero) if the firm's reported emissions abatement falls above (below) the assigned target, while the exit variable is the primary outcome indicator equal to one (zero) if the firm terminates permanently the CCAs agreement by 2015. The first and second columns show how firm-level performance and exit respectively correlate with the assigned industry-level targets. The third and fourth columns show how target-residual variation in performance and exit respectively correlate with a selected set of firm's characteristics. Specifically, recalling that cost-efficient targets should ideally predict most of the variation in firms' exit choices by reflecting their exit thresholds, I expect firm-level determinants of residual variation in exit to improve welfare once included in the regulator's information set for the determination of the targets. To preserve the parsimony of the model, I only introduce historical emissions intensity and trade intensity as canonical proxies of the firm's historical exposure to emissions leakage, but I also add a proxy for the firm's availability of internal finance to capture observable variation in emissions adjustment effects. The construction of the variables is reported in the data appendix G.

Table 3.2. shows that historical emissions intensity does not affect firm's performance within

Table 3.2. *Regression Table.*

Linear regressions with clustered standard errors (firm-level). The column (Residual Performance) reports firm-level performance in excess of the amount predicted by the target. The column (Excess Participation) reports firm-level exit in excess of the exit amount by the target. Details on the construction of the regressors are reported in the data appendix G. *,**,*** indicate statistical significance at 1st, 5th, and 10th level respectively.

Variables	Performance	Exit	Residual Performance		Residual Exit	
Target	-0.90**	-2.88***				
	(0.37)	(0.27)				
Internal Finance			0.02**	0.02**	-0.03***	-0.02**
			(0.01)	(0.01)	(0.00)	(0.01)
Emission Intensity			0.00	0.00	0.01***	0.01**
			(0.00)	(0.00)	(0.00)	(0.00)
Trade Intensity			0.05*	0.05	0.09***	0.07**
			(0.03)	(0.04)	(0.03)	(0.03)
Industry Effects (Sic 2 Digit)			No	Yes	No	Yes
$\mathcal{R}^2$	0.01	0.05	0.01	0.07	0.02	0.12
Observations	1,639	2,130	1,639	1,639	2,130	2,130
Clusters	1,474	1,856	1,474	1,474	1,856	1,856

the agreement, meaning that everything else equal, historical emissions have a negligible effect on the firm's optimal abatement rate. According to the model, this implies that the emissions abatement cost curve is roughly linear in historical emissions. On the other hand, consistently with related literature on the subject, both emissions intensity as well as trade intensity appear to be strongly positively correlated with firm's exit, suggesting that those variables are most likely to affect the extensive margin component of the exit threshold. Conversely, internal finance appears a significant determinant of firm-level performance within CCAs, suggesting that emissions abatement costs are sensible to firm's financial constraints. Importantly, this finding is supported by evidence collected from firms' own responses in the CCAs' questionnaire,[41] as well as in line with a recent study by Antoniou, Delis, Ongena, and Tsoumas [2020] on the European cap and trade

[41] As reported in the data appendix G, over 70% of respondent firms stated that *whether or not the investment required external finance* was a critical factor when deciding if implement physical or financial compliance with the target., notably more important that the cost of fossil-fuel input itself.

market.

Quantitative Exercise

For each firm i in sector j, denote y_{ij1} as the model-implied participation choice which follows the specification

$$y_{ij1}(\gamma, \beta) = 1\{\mathbb{E}[z_{ij}(\gamma, \beta)] - \bar{\delta}_j + \tilde{u}_{ij1} \geq 0\} \tag{3.18}$$

with $\mathbb{E}[z_{ij}(\gamma, \beta)]$ the expected exit threshold from (3.15) specified as

$$\mathbb{E}[z_{ij}(\gamma, \beta)] = exp(\gamma^T[1; \psi_{ij}])(s_j + 0.5a) + \beta^T[1; z_{ij}] \tag{3.19}$$

where term s_j is the industry-specific fossil-fuel implied cost of carbon whose construction is reported in the data appendix G, a is the fixed permit price, ψ_{ij} is the normalized proxy for internal finance, z_{ij} is the vector of normalized trade intensity and emissions intensity respectively, $\bar{\delta}_j$ is the observed emission reduction target, and $\tilde{u}_{ij1}$ is a de-meaned error term distributed as $\mathcal{N}(0, \sigma_1^2)$. Specifically, $\tilde{u}_{ij1}$ includes potentially three sources of uncertainty which are the firm's private type, the unpredictable exit cost shock, as well as an independent measurement error term.[42]

For each firm i in sector j, denote y_{ij2} as the model-implied conditional performance which follows the specification

$$y_{ij2}(\gamma) = \begin{cases} 1\{\mathbb{E}[\delta^*_{ij}(\gamma)] - \bar{\delta}_j + \tilde{u}_{ij2} > 0\} & \text{if} \;\; y_{ij1}(\gamma, \beta) = 1 \\ 0 & \text{if} \;\; y_{ij1}(\gamma, \beta) = 0 \end{cases} \tag{3.20}$$

where $\mathbb{E}[\delta^*_{ij}(\gamma)]$ is firm i's optimal expected abatement, specified as

$$\mathbb{E}[\delta^*_{ij}(\gamma)] = exp(\gamma^T[1; \psi_{ij}])(s_j + a) \tag{3.21}$$

while $\tilde{u}_{ij2}$ is a firm-specific error term distributed as $\mathcal{N}(0, \sigma_2)$ which encompasses the firm's private type as well as an independent error term.

I first estimate the set of parameters $\Theta_1 = \{\beta, \gamma, \sigma_1\}$ by maximizing the log likelihood of the

[42]The assumption is that the total error is homoskedastic. The unpredictable exit cost shock is interpreted as a determinant of exit which is unrelated to the firm's cost of compliance with the regulation.

participation choice

$$\mathcal{L}_1(\Theta_1) = \sum_{i=1}^{n} \hat{y}_{ij1} \ \ln\Phi_{ij}(\Theta_1) + (1 - \hat{y}_{ij1}) \ \ln(1 - \Phi_{ij}(\Theta_1) \tag{3.22}$$

with $\hat{y}_{ij1}$ the observed participation choice in CCAs and $\Phi_{ij}(\Theta_1)$ the standard cumulative distribution function as specified in the data appendix G. I then estimate the remainder parameters $\Theta_2 = \{\sigma_2, \rho_{12}\}$ with $\rho_{12} = corr(\sigma_2, \sigma_1)$ by maximizing the approximated log likelihood of the conditional performance

$$\mathcal{L}_2(\Theta_2) = \sum_{i=1}^{n} \{\hat{y}_{ij1} = 1\}\big(\hat{y}_{ij2} \ \ln\Phi_{ij}(\Theta_2|\hat{\Theta}_1) + (1 - \hat{y}_{ij2}) \ \ln(1 - \Phi_{ij}(\Theta_2|\hat{\Theta}_1))\big) \tag{3.23}$$

where $\hat{y}_{ij2}$ is the observed performance in CCAs and $\hat{\Phi}_{ij}(\Theta_2)$ is the conditional performance probability predicted by the first stage estimation $\hat{\Theta}_1$ as reported in the data appendix G. The estimated coefficients along with their standard errors are reported in Table 3.3. below.

Table 3.3. *Model Parameters*

The Table reports coefficient estimates and standard errors obtained by maximizing log-likelihood of participation choice (stage I) and conditional performance respectively (stage II). Details of the estimation process are reported in the data appendix G.

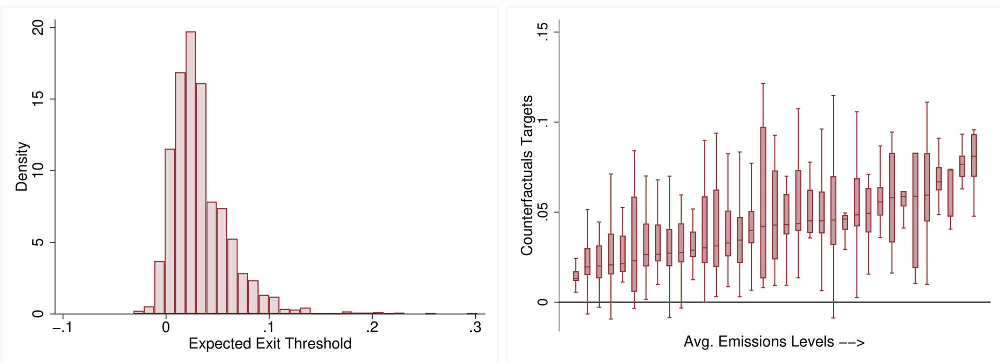
Parameter	Explanation	MLE Estimation	Coeff.	Std. Err.
β_0	Constant	I	0.05***	(0.01)
β_1	Trade intensity	I	-0.02***	(0.00)
β_2	Emissions intensity	I	-0.01***	(0.00)
γ_0	Fossil-fuel implied cost of carbon	I	-2.92***	(0.99)
γ_1	Internal finance	I	1.24***	(0.19)
σ_1	Exit volatility	I	0.13***	(0.01)
σ_2	Performance volatility	II	0.20***	(0.04)
ρ	Latent correlation	II	0.28***	(0.05)

Coefficient estimates from the first estimation confirm that both higher trade intensity and higher emissions intensity predict lower participation in CCAs, while higher availability of internal finance predicts higher participation in CCAs through decreased emissions adjustment costs. Interestingly as revealed by the coefficient γ_0, industry-level price of carbon implied by fossil-fuel energy consumption seems to be strongly negatively correlated with participation in CCAs, meaning that firms facing lower energy input costs are more likely to stay in the agreement. The left-hand plot in Figure 3.5 shows the distribution of the predicted exit threshold that derives from these estimates. As observed, the expected exit threshold averages slightly below 5% while varies between -3% and 30% across firms in CCAs depending on the input variables. I therefore feed the predicted exit thresholds into the expression (3.16) to determine counterfactual cost-efficient targets under the assumption that each firm's contribution to welfare is well approximated by its historical operating capital (e.g. weights are set equal to the inverse of the firm's historical emissions intensity). The coefficient λ is therefore determined numerically so that carbon subsidies implied by cost-efficient targets equate the government budget used in the policy $D = 840\text{m£}$, which I simply estimate using historical emissions levels, observed targets and recalling that the permit price $a = 12\text{£}/CO_2e$. To get a sense of the magnitude of this budget, it is worth noting that such a figure corresponds to roughly 50% of the total revenues from the CCL over the same target period, as collected from aggregate statistics provided by BEIS.

The right plot in Figure 3.5 plots the estimated within-industry distribution of cost-efficient targets against increasing average emissions levels of the industry. As observed, targets are now *increasing* on average as a function of average emissions levels in the industry. This because according to the coefficient estimates, the negative marginal effect of historical emissions intensity on the firm's exit threshold is more than offset by the positive effect that historical emissions have on the budget constraint (e.g. the effect introduced by the firm-specific weight). However, targets vary consistently within industries, showing once again that allocation rules based on industry-level characteristics are missing welfare-improving information. Finally, I use the explicit expression in

Figure 3.5 *Estimated Threshold and Cost-Efficient Targets*

The left plot shows the distribution of the expected exit threshold as estimated from firms' participation choices in CCAs. The right plot shows the distribution of cost-efficient targets within industry sorted by average emissions levels in the industry.



(3.10) to quantify the welfare loss induced by the allocation of the observed targets instead of the ones implied by the model. A simple calculation shows that only including firm-level observable determinants of exit would improve welfare up to 7% in expectation, of which a 3% improvement is uniquely attributed to the inclusion of firms' financial constraints. By means of the estimated latent correlation between abatement performance and exit and the explicit expression in (3.17), one can then simulate the expected welfare improvement that the regulator would get by taking count of unobserved determinants of emissions abatement correlated with exit. From this last exercise, it emerges that including the latent emissions abatement factor can improve welfare of a further 12% in expectation. The quantitative exercise reveals that carbon pricing policies should include firm-level information about carbon leakage incentives and should be designed so that to induce truthful reporting of private emissions abatement costs.

3.4 Conclusions

This study uses a model and data from a large-scale corporate climate regulation in the United Kingdom to investigate the welfare losses that an imperfectly informed regulator incurs when subsidizing firms at risk of carbon leakage. In presence of a binding budget constraint on the pollution subsidies, cost-efficiency requires knowledge of carbon leakage propensities across firms, yet allocation rules continue to rely on "one size fits all" principles that disregard of variation in firm-level relocation incentives. In line with evidence collected from the UK climate policy, the study shows that disregarding of carbon emissions adjustments when determining leakage propensities is most likely to favour emissions intensive industries. A quantitative exercises suggests that simply including firm-level variation in access to external finance improves expected welfare of 3%, whereas accounting for a latent factor in carbon emissions abatement adds a further 12% gain in expected welfare. The quantitative exercise reveals that emissions intensive firms should not be always ranked at the highest risk of carbon leakage, and that carbon pricing policies should be designed so that to induce truthful reporting of private emissions abatement costs.

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Appendices

A Data Appendix

Institutional Details. The issuance of green/social/sustainability bonds as well as sustainability-linked bonds is governed by the principles put forth by the International Capital Market Association (ICMA), summarized in Table A.4. Under the GBPs, SBPs, and SBGs, an amount equal to the net bond proceeds is dedicated to financing elibigle projects (from which the term use of proceeds bonds), while under the SLBPs, proceeds are primarily for the general purpose of an issuer in pursuit identified Key Performance Indicators (KPIs) and Sustainable Performance Targets (SPTs). Guidance regarding the issuance of green loans and sustainability-linked loans is provided by the Loan Market Association (LMA), materialm it is generally less stringent and more customized than that applicable to their public counterpart. For example, verification of performance reports is negotiated and agreed between the borrower and lenders on a transaction-by-transaction basis, and is only recommended when reporting about KPIs is not made publicly available or otherwise accompanied by an audit/assurance statement.

Table A.4 *The Principles by ICMA*

The Table reports the key components of the Green Bond Principles (GBPs), Social Bond Principles (SBPs), Sustainability Bond Guidelines (SBGs), and Sustainability-Linked Bonds Principles (SLBPs) resepctively as issued by ICMA. Further detils can be found at *https://www.icmagroup.org/sustainable−finance/.*

GBPs/SBPs/SBGs	**SLBPs**
1) Use of proceeds for green/social/sustainable projects	1) Selection of Key Performance Indicators (KPIs)
2) Process for project evaluation and selection	2) Calibration of Sustainability Performance Target (SPTs)
3) Management of proceeds	3) Bond characteristics (contingency)
4) Reporting of proceeds	4) Reporting performance on the KPI
	5) Verification of KPI performance against the SPT

Securities data. We compile the dataset of sustainable corporate debt using Bloomberg's fixed income database. We extract all corporate bonds and loans for which the field "Green Instruments Indicator", "Social Instrument Indicator", "Sustainability Instrument Indicator", "Sustainability Linked Bond / Loan Indicator" is "Yes". We exclude securities whose issuer's Bloomberg Industry Classification System BICS is "Government".[43] Bloomberg applies a green/social/sustainability indicator if the issuer self-report (and/or if relevant documentation is available) that 100% of the

[43] Those issuers include development banks and supranational entities which qualify as corporate due to their private status but are not corporations in a traditional sense.

proceeds of the debt instrument are devoted to predetermined environmental/social/sustainability-oriented activities. Bloomberg's indicator therefore follows loosely the reference guidelines issued by the ICMA corresponding to each of those categories, in that only the component 1) out of the four key components in Table A.4 is captured by the indicator.[44] In a similar manner, Bloomberg applies a sustainability-linked label if the issuer self-reports (and/or if relevant documentation is available) that the debt instrument is linked to a sustainability performance metric, which is again only one of the five key requirements summarized in Figure 1.

Bonds. As Panel A in Table A.5 indicates, our global sample, which runs from January 2013 through April 2021, contains 4,618 "sustainable" bonds (which comprise 3,758 green, 306 social, 391 sustainable bonds, and 149 sustainability-linked bonds) versus 1,055,033 ordinary corporate bonds. The Table shows that relative to ordinary bonds, sustainable bonds are larger in terms of amount issued ($289 mil versus $97 mil), a fact that may owe something to the fixed costs of certifying their green/social/sustainable status. On average, sustainable bonds have a lower coupon rate (about 1.8% difference), and more likely to have a fixed coupon rate than ordinary bonds (76% vs 63% have a fixed coupon, respectively). Consistently with early evidence in Baker et al. [2018], they also tend to have longer maturity and higher credit rating. The maturity gap is perhaps not surprising given that green and sustainability-oriented projects tend to have a longer payback horizon than general corporate projects not aimed at helping the company transition to a more sustainable business model. On the other hand as summarized by Figure A.6, differences in credit ratings are uniquely driven by the class of non-contingent green debt, namely green, social, and sustainable bonds, since sustainability-linked bonds have considerably lower ratings than the universe of bonds issued in the same period.

Loans. As Panel B in Table A.5 indicates, our total sample contains 3,971 "sustainable" loans (consisting of 3,251 green loans and 720 sustainability sustainability-linked loans) versus 108,592 ordinary corporate loans. The Table shows that, similarly to their bonds counterpart, sustainable loans are larger in terms of amount issued and longer in maturity than ordinary loans. Interestingly, the difference in maturity seems to be mostly driven by green loans, as the new class of sustainability-linked loans appear to have an average maturity more similar to ordinary loans. The interest rates associated with sustainable loans is lower than that of ordinary loans (this difference

[44] See https://www.icmagroup.org/sustainable-finance/the-principles/ for a complete list of the ICMA reference guidelines, and Shurey (2016) for a *Guide to Green Bonds on the Bloomberg Terminal.*

is particularly pronounced for sustainability-linked loans), and similarly to ordinary loans, sustainable loans predominantly have a floating interest rate (98% for sustainable loans and 96.5% for ordinary loans). Another interesting fact is that unlike green loans, the majority of sustainability-linked loans is of revolving type. Related to this fact, it is worth mentioning that approximately 20% of the existing sustainability-linked loans were issued as ordinary or green loans, and then later linked to a metric of sustainability performance. Sustainable loans have a poorer credit coverage compared to ordinary loans but a slightly higher credit rating, and unlike their public counterpart, SLLs have a similar credit rating compared to green loans.

Performance Metrics. We obtain data on the sustainability performance targets (SPTs) underlying sustainability-linked loans and bonds from Bloomberg New Energy Finance (NEF). Table A.6 breaks down the available SPTs[45] by major categories, namely SPTs based on public Environmental, Social, and Governance (ESG) scores, as well as SPTs based on specific environmental, social, and governance metrics respectively. Worth noting is that 64% of the SPTs are written on environmental metrics, of which 44% are GHGs emissions, a clear evidence of the centrality of climate change with respect to other sustainable issues. In decreasing order, the SPTs based on ESG scores account for roughly 17% of the total sample (which most of those scores being provided by Sustainalytics, the same rating provider that we use in our empirical analysis), whereas social and governance metrics account for roughly 15% and 4% of the remaining SPTs, respectively.

[45] One must note that there is not a one-to-one correspondence between SPTs and securities in that one or more SPTs can be associated to the same sustainability-linked bond or loan.

Table A.5 *Corporate Sustainable Bonds and Loans*

The Table shows summary statistics on corporate bonds (panel A) and loans (panel B) issued between January 2013 and April 2021 as collected from Bloomberg fixed income search. The first column refers to the selected sample of green, social, sustainable, and sustainability-linked securities. The second column refers to the sub-sample of sustainability-linked securities. The third column refers to the entire universe of corporate bonds and loans. The variables Use of Proceeds, Project Selection, Management and Reporting are dummy variables referring to compliance with the four principles issued by ICMA (as observed from ESG reports or other available sources), whether the variable assurance is an indicator equal to 1 if there is third-party assurance of compliance with the principles.

Panel A: Bonds	**Green/Social/Sustainable/Sustainability-linked**	**Sustainability-linked**	**Ordinary**
Variable	**Mean**	**Mean**	**Mean**
Amount Issued ($ mil)	289	425	97
Coupon Rate (%)	2.5	1.9	4.2
Maturity (years)	8.2	7.7	3.2
Project Selection (%)	96.9	1.3	0.4
Management (%)	95.5	1.3	0.3
Reporting (%)	95.4	1.3	0.3
Assurance (%)	85.1	6.7	0.3
Securities	4,618	149	1,055,033

Panel B: Loans	**Green/Sustainability-linked**	**Sustainability-linked**	**Ordinary**
Variable	**Mean**	**Mean**	**Mean**
Loan Tranche Size ($ mil)	214	695	326
Is Loan Revolving (%)	18.2	57.2	25.9
Coupon Rate (%)	2.6	1.9	4.5
Maturity (years)	15.7	7.8	8.6
Project Selection (%)	7.9	0.7	0.3
Management (%)	6.6	0.7	0.2
Reporting (%)	5.1	1.1	0.2
Assurance (%)	2.5	1.0	0.1
Securities	3,971	720	108,592

Figure A.6 *Bonds Credit Ratings*

The histogram shows the distribution of Standard & Poor (S&P) credit ratings of corporate bond securities issued between January 2013 and April 2021. Grey bars refer to the entire universe of corporate bonds, green bars refer to the subset of corporate bonds which are labelled as Green, Social, or Sustainable, whereas red bars refer to the subset of corporate bonds which are labelled as Sustainability-linked.

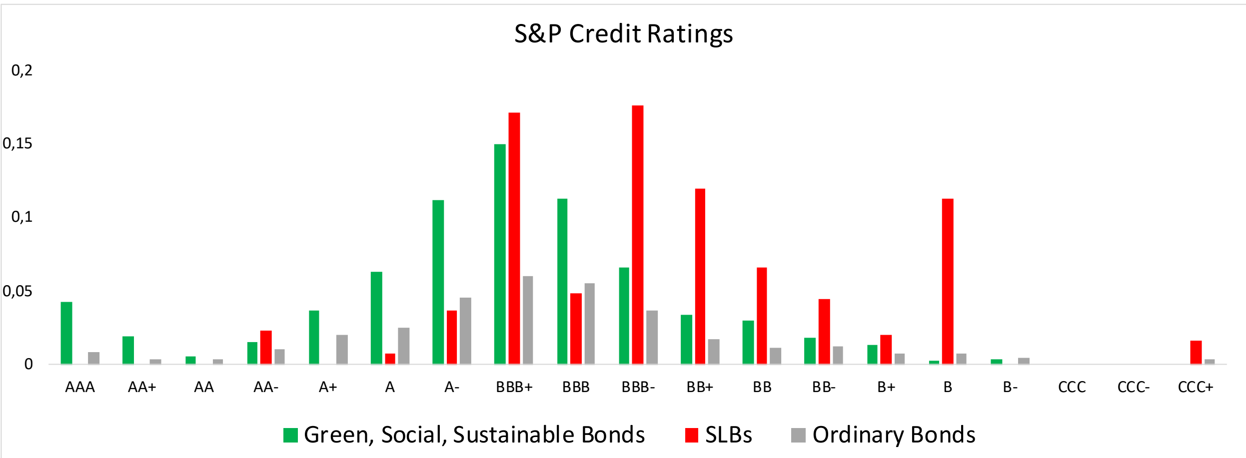


Figure A.7 *Bonds Holders*

The histogram shows the distribution of holding shares of corporate bond securities issued between January 2013 and April 2021 by type of investor. Grey bars refer to the entire universe of corporate bonds, green bars refer to the subset of corporate bonds which are labelled as Green, Social, or Sustainable, whereas red bars refer to the subset of corporate bonds which are labelled as Sustainability-linked.

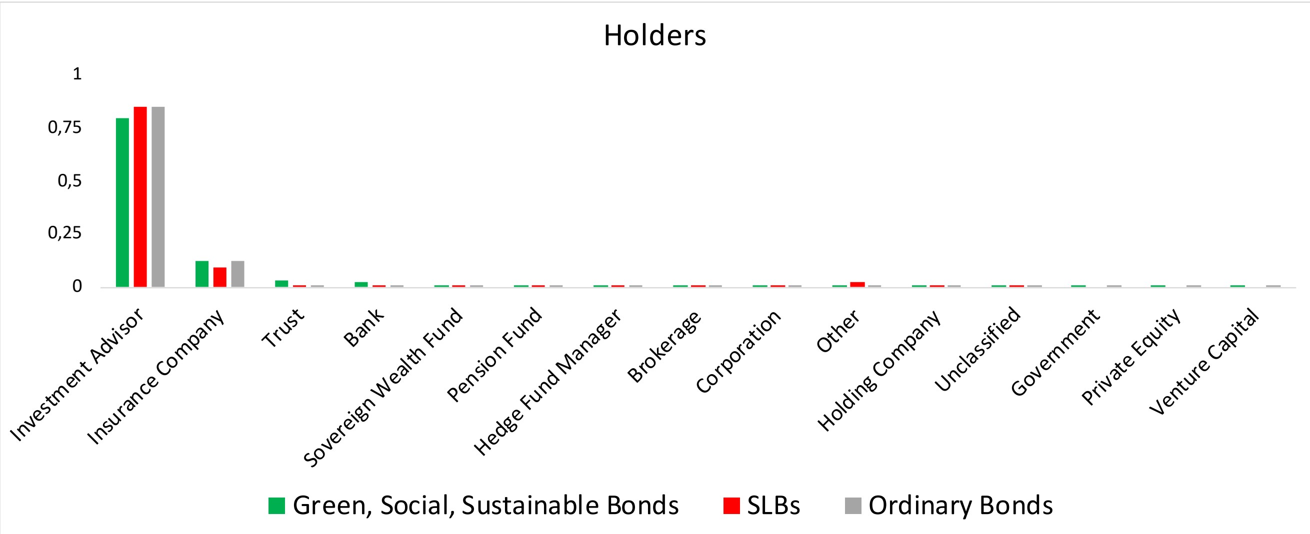


Figure A.8 *Issuances by Industry*

The top histogram shows the number of "green" issuers in the Bloomberg/S&P Trucost matched dataset by Global Industry Classification (GIC) Sectors. The bottom histogram shows to the conditional proportion of contingent and non-contingent debt in red and green respectively by GIC Sectors.

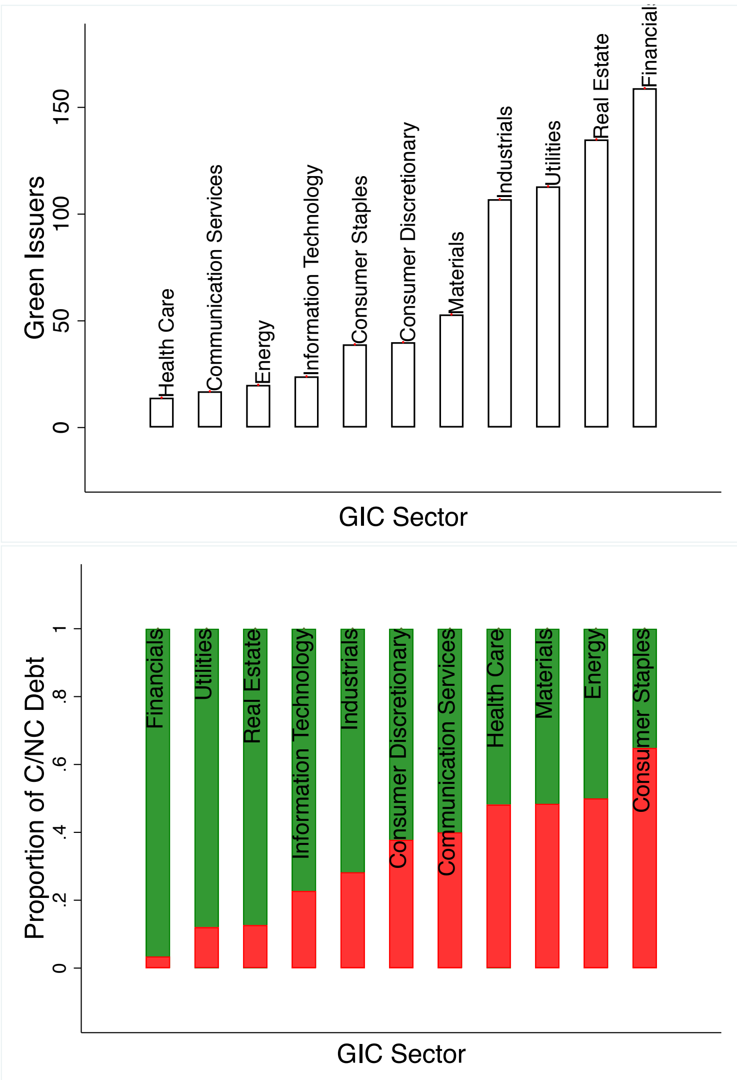


Table A.6 *Sustainability Performance Targets (SPTs)*

The table breaks down the target performance metrics linked to Sustainability-Linked Loans (SLLs) and Bonds (SLBs) by categories types (general ESG Scores, Environmental metrics, Social metrics, Governance metrics) and sub-categories respectively. Data are collected from Bloomberg NEF and refer to issuance of SLLs as of May 2021.

ESG Score	Environmental Metrics	Social Metrics	Governance Metrics
143	537	124	38
• Sustainalytics 31%	• GHGs 44%	• Work Accidents 21%	• Female Board 26%
• GRESB 12%	• Renewables 16%	• Labor Rights 11%	• Other 74%
• EcoVadis 10%	• Waste 14%	• Female Staff 6%	
• Vigeo Eiris 6%	• Energy Efficiency 7%	• Education 5%	
• Other/Unknown 41%	• Water 5%	• Social Returns 3%	
	• Transport 3%	• Disabilities 2%	
	• Other/Unknown 11%	• Other/Unknown 51%	

Figure A.9 *Targets by Industry*

The bar plot shows the relative proportion of the four target performance categories (e.g. general ESG Score, Environmental metrics, Social metrics, and Governance metrics respectively) across industry sectors ordered by increasing number of SLLs and SLBs issuances.

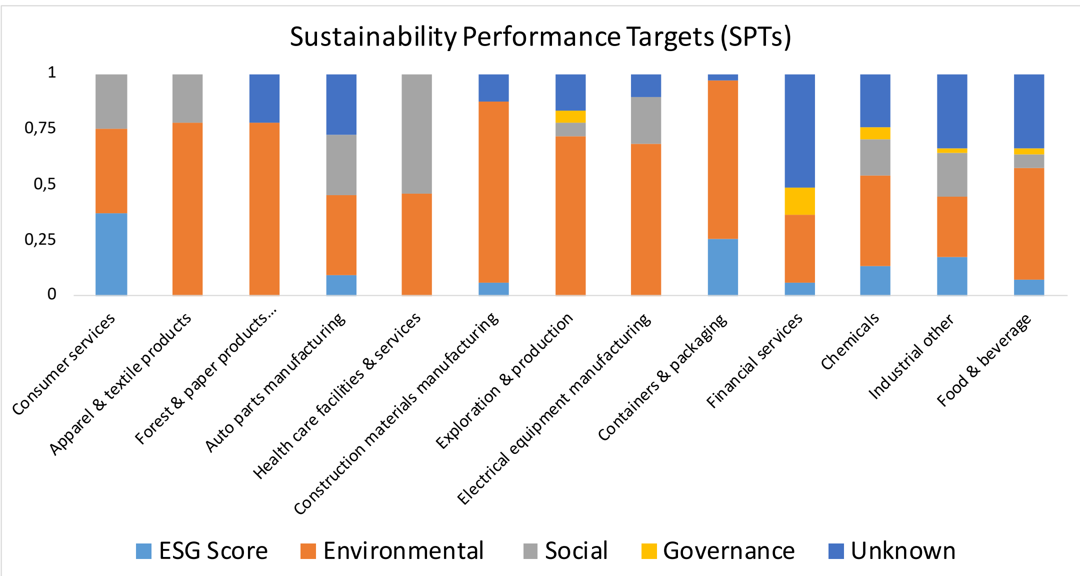


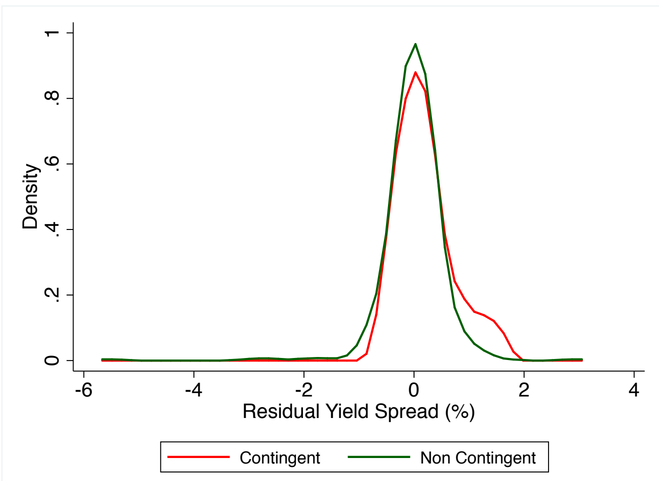
Table A.7 *Action and Distortion Cost - Correlations*

The table shows correlations (linear regressions) from the firm's distortion cost and action cost as proxied by historical emissions intensity and propensity of greenwashing respectively. Other controls are collected from Bloomberg/Sustainalytics/S&P Trucost merged dataset. *,**,*** indicate statistical significance at the 10%, 5% and 1% level respectively.

	Cost of Distortion		
Cost of Action	- 0.44**	-0.58*	0.62*
	(0.21)	(0.36)	(0.39)
Log Revenues			-2.61***
			(0.34)
EBIT to Revenues Ratio			-3.12**
			(1.48)
Debt to Value Ratio			1.06
			(2.49)
Self-Disclosure of Emissions			-0.05***
			(0.01)
Intercept	Yes	Yes	Yes
Industry Dummy	No	Yes	Yes
Location Dummy	No	No	Yes
$\mathcal{R}^2$	0.01	0.26	0.41
Unique Firms	476	476	476

Figure A.10 *Spread Differentials - Regression Residuals*

The plot shows the distribution of residuals in green-conventional bond green premia grouped by type of green security (e.g. contingent green bonds in red and non-contingent green bonds in green respectively). Residuals are obtained from the regression of yield spreads on bond characteristics where the dummy variable Contingent Debt has been excluded.



B Model Appendix

Proposition 1. The financing choice can be expressed as

$$y^* = cg \ \text{ iff } \ \mathbb{E}[\mathcal{U}^f_{cg}] > \mathcal{U}^f_v + \max\{0, \frac{1}{2\theta} - \alpha\}. \tag{24}$$

If $\psi = +\infty$, then

$$\mathbb{E}[\mathcal{U}^f_{cg}] = \mathcal{U}^f_v + \mathbb{E}[(\frac{1}{2\theta} + \sigma\tilde{z} - \alpha)^+] \tag{25}$$

rewriting condition (24) and applying the Jensen's inequality

$$\begin{aligned}\mathbb{E}[(\frac{1}{2}\frac{1}{\theta} + \sigma\tilde{z} - \alpha)^+] - \max\{0, \frac{1}{2}\frac{1}{\theta} - \alpha\} &\geq \mathbb{E}[(\frac{1}{2}\frac{1}{\theta} + \sigma\tilde{z} - \alpha)^+] - \frac{1}{2}\frac{1}{\theta} + \alpha \\ &> \frac{1}{2}\frac{1}{\theta} + \sigma\mathbb{E}[\tilde{z}] - \frac{1}{2}\frac{1}{\theta} = 0\end{aligned} \tag{26}$$

from which the proof follows. If $\psi < +\infty$, then

$$\mathbb{E}[\mathcal{U}^f_{cg}] = \mathcal{U}^f_v + \mathbb{E}[(\frac{1}{2\theta} - \frac{\sigma^2}{2\psi} + \sigma\tilde{z} - \alpha)\{\frac{1}{2\theta} + \frac{\sigma^2}{2\psi} + \sigma\tilde{z} - \alpha > 0\}] \tag{27}$$

For any (σ, θ, α), it holds that

$$\lim_{\psi \to 0} \mathbb{E}[(\frac{1}{2\theta} - \frac{\sigma^2}{2\psi} + \sigma\tilde{z})1\{\frac{1}{2\theta} + \frac{\sigma^2}{2\psi} + \sigma\tilde{z} > 0\}] = -\infty \tag{28}$$

since the project will be picked with probability one whereas the distortion discount will approach infinite. This implies that for any (σ, θ, α)

$$\lim_{\psi \to 0} \mathbb{E}[\mathcal{U}^f_{cg}] < 0 < \max\{0, \frac{1}{2\theta} - \alpha\} \tag{29}$$

which by definition of the limit proves the result. On the other hand for any (σ, θ, α) one has

$$\lim_{\psi \to +\infty} \mathbb{E}[(\frac{1}{2\theta} - \frac{\sigma^2}{2\psi} + \sigma\tilde{z} - \alpha)1\{\frac{1}{2\theta} + \frac{\sigma^2}{2\psi} + \sigma\tilde{z} - \alpha > 0\}] = \mathbb{E}[(\frac{1}{2\theta} + \sigma\tilde{z} - \alpha)^+] \tag{30}$$

which by definition of the limit and the result stated in (129) proves the result.

Proposition 2. Denote the type $k \in [0,1]$ such that $\theta_k = \theta/k$ and $\psi_k = \psi/(1-k)$, with

$0 < 2\theta\alpha < 1$, $\psi > 0$ and $\sigma > 0$. The utility from issuance of a non-contingent contract reads

$$\mathcal{U}_v^f + \max\{\mathcal{U}_g^f(k) - \mathcal{U}_v^f, 0\} = \mathcal{U}_v^f + \max\{\frac{k}{2\theta} - \alpha, 0\} \tag{31}$$

which is a piecewise function of k, whereas

$$\begin{aligned}\mathbb{E}[\mathcal{U}_{cg}^f(k)] &= \mathcal{U}_v^f + \mathbb{E}[(\frac{k}{2\theta} - \frac{1}{2}\frac{\sigma^2(1-k)}{\psi} + \sigma\tilde{z} - \alpha)1\{\frac{k}{2\theta} + \frac{1}{2}\frac{\sigma^2(1-k)}{\psi} + \sigma\tilde{z} - \alpha > 0\}] \\ &= \mathcal{U}_v^f + (\frac{k}{2\theta} - \frac{1}{2}\frac{\sigma^2(1-k)}{\psi} - \alpha)F(k,\sigma,\theta,\psi,\alpha) + \sigma f(k,\sigma,\theta,\psi,\alpha)\end{aligned} \tag{32}$$

where $F(k,\sigma,\theta,\psi,\alpha) = \mathcal{N}(\frac{1}{2}\frac{k}{\sigma\theta} + \frac{1}{2}\frac{\sigma(1-k)}{\psi} - \alpha)$ is the cumulative normal distribution and $f(k,\sigma,\theta,\psi,\alpha) = F^{'}(k,\sigma,\theta,\psi,\alpha)$ is the density function. Simplifying, the net-profits from issuance of the contingent contract read

$$\begin{cases} kF_k\frac{1}{2\theta} - (1-k)F_k\frac{\sigma^2}{2\psi} - \alpha F_k + \sigma f_k \; if \; k \in [0, 2\alpha\theta] \\ k(F_k - 1)\frac{1}{2\theta} - (1-k)F_k\frac{\sigma^2}{2\psi} - \alpha(F_k - 1) + \sigma f_k \; if \; k \in (2\alpha\theta, 1] \end{cases} \tag{33}$$

When the distortion cost ψ is low, preferences for the contingent contracts are strictly increasing in k. This is because the net profits in (33) are approx $-(1-k)F_k\frac{\sigma^2}{2\psi}$, whose derivative $-F_k^{'}(1-k)\frac{\sigma^2}{2\psi} + F_k\frac{\sigma^2}{2\psi} > 0$ since $F_k^{'} < 0$ for each $k \leq 1$ when ψ is low. In such a scenario, it exists a $\overline{k}$ and $\underline{k}$ such that if $k > \overline{k}$ then $y_k = cg$, if $k \in [\underline{k}, \overline{k}]$ then $y_k = g$, whereas if $k < \underline{k}$ then $y_k = v$, which proves the result. When the distortion cost ψ is high, then the profits in (33) are strictly increasing in k for $k \leq 2\alpha\theta$, whereas they are strictly decreasing in k for $k \geq 2\alpha\theta$. This because the expression in (33) simplifies to

$$\approx \begin{cases} kF_k\frac{1}{2\theta} - \alpha F_k + \sigma f_k \; if \; k \in [0, 2\alpha\theta] \\ k(F_k - 1)\frac{1}{2\theta} - \alpha(F_k - 1) + \sigma f_k \; if \; k \in (2\alpha\theta, 1] \end{cases} \tag{34}$$

deriving the first term with respect to k, one gets

$$\begin{aligned}\frac{\partial}{\partial k}(kF_k\frac{1}{2\theta} - \alpha F_k + \sigma f_k) &= F_k\frac{1}{2\theta} + F_k^{'}(\frac{k}{2\theta} - \alpha) + \sigma f_k^{'} \\ &= F_k\frac{1}{2\theta} + \frac{1}{\sigma}f_k(\frac{k}{2\theta} - \alpha)\frac{1}{2\theta}(\frac{k}{2\theta} - \alpha) - \sigma f_k\frac{1}{\sigma}(\frac{k}{2\theta} - \alpha)\frac{1}{2\theta} \\ &= F_k\frac{1}{2\theta} > 0\end{aligned} \tag{35}$$

which is strictly positive, whereas deriving the second term with respect to k, one gets

$$\begin{aligned}\frac{\partial}{\partial k}(k(F_k-1)\frac{1}{2\theta}-\alpha(F_k-1)+\sigma f_k) &= \frac{\partial}{\partial k}(kF_k\frac{1}{2\theta}-\alpha F_k+\sigma f_k)-\frac{1}{2\theta} \\ &= F_k\frac{1}{2\theta}-\frac{1}{2\theta}<0\end{aligned} \tag{36}$$

which is strictly negative. Importantly though, given that manipulation is negligible, net profits are overall above zero (e.g. Proposition 1 applies) and therefore such that all firms issue the contingent contract. In such a scenario, $k=\overline{k}=0$, which again proves the result. On the other hand, when the distortion cost is neither high nor low, following the previous discussion, net profits in (33) are strictly increasing in k for $k\in[0,2\alpha\theta]$, whereas they can be decreasing, increasing, or non-monotonic as a function of k for $k\in(2\alpha\theta,1]$. Specifically, there is a region of other model parameters under which preferences for the contingent contract are u-shaped in k. In such a case, it exists a $\underline{k}<\overline{k}$ such that if $k<\underline{k}$ then $y_k=v$ whereas if $k>\overline{k}$ then $y_k=cg$, it may exist a $k^{'}<\overline{k}$ such that if $k\in[\underline{k},k^{'}]$ then $y_k=cg$ whereas if $k\in[k^{'},\overline{k}]$ then $y_k=g$.

Proposition 3. In presence of asymmetric information, we solve for a semi-separating Perfect Bayes Equilibrium (PBE) of a signalling game where the first mover (the firm) has infinite types $k\sim\mathcal{U}[0,1]$ and two moves (issue a contingent contract or the best of the non-contingent contract) $y(k)=\{max(g,v),cg\}$, whereas the second mover (investor) has one type and two moves (accept or refuse the proposed contract) $b=\{1,0\}$ and belief over the firm's type $\beta(k)\sim\mathcal{U}[2\theta\alpha,1]$ if $g>v$, and $\beta(k)\sim\mathcal{U}[0,2\theta\alpha]$ if $g<v$. A PBE requires that the firm's issuance strategy is sequentially rational – that is at each information set in which the firm moves, the firm maximizes its expected utility anticipating the investor's beliefs at the information set, and that the investor updates its belief in a Bayesian manner.

A first thing to note is that, independently of the issuance choice, the firm is strictly better off when the investor accepts the proposed contract instead of when it refuses it. This because it holds that $\min\{\mathbb{E}[\mathcal{U}^f_{cg}(k)],\mathcal{U}^f_g(k),\mathcal{U}^f_v\}\geq R>0$. Consequentely, the firm will always propose a contract rate so as to satisfy the investor's participation constraint – meaning that the investor always buys the contract $b=1$ in equilibrium.

We consider the optimal contracting problem from the perspective of a high type firm that knows that if it offers a contract cg, it will be mimicked by low type firms, so that it is always pooled with low firms in the same observable group $\mathcal{K} = [2\alpha\theta, k)$ if $k > 2\theta\alpha$ or $\mathcal{K} = [0, k)$ if $k < 2\theta\alpha$. The reason why low firms imitate high firms is that a different strategy would reveal that they are low firms with higher manipulation incentives. Let us first focus on the case where $k > 2\alpha\theta$. Following the discussion in Mailath [1987], for $(y(k), \beta(k))$ as defined in the main text to be a PBE it is sufficient to prove that the single-crossing property is verified, meaning that

$$\frac{\partial}{\partial k}\big(\mathbb{E}[\mathcal{U}^f_{cg}(k)|\beta(k|\mathcal{K})] - \mathcal{U}^f_g(k)\big) \leq 0 \tag{37}$$

Let us first decompose the expected utility upon issuance of cg in presence of asymmetric information

$$\begin{aligned}
\mathbb{E}[\mathcal{U}^f_{cg}(k)|\beta(k|\mathcal{K})] &= \mathbb{E}[\mathcal{U}^f_{cg}(k)] + \bar{\rho}^{cg}_k - \int_{2\alpha\theta}^{k} \bar{\rho}^{cg}_k dk \\
&= (\frac{k}{2\theta} - \alpha)F_k - \frac{1}{2}\frac{\sigma^2(1-k)}{\psi}F_k + \sigma f_k + \frac{\sigma^2(1-k)}{\psi}F_k - \frac{1}{k-2\alpha\theta}\int_{2\alpha\theta}^{k}\frac{\sigma^2(1-k)}{\psi}F_k dk \\
&= (\frac{k}{2\theta} - \alpha)F_k - \frac{1}{2}\frac{\sigma^2}{\psi}F_k(1-2\theta\alpha) + \sigma f_k
\end{aligned} \tag{38}$$

therefore taking the derivative of (37) with respect to k, one gets

$$\begin{aligned}
\frac{\partial}{\partial k}\big(\mathbb{E}[\mathcal{U}^f_{cg}(k)|\beta(k|\mathcal{K})] - \mathcal{U}^f_g(k)\big) &= -\frac{1}{2}\frac{1}{\theta}(1-F_k) + F^{'}_k(\frac{k}{2\theta} - \alpha - \frac{\sigma^2}{2\psi}(1-2\theta\alpha)) + \sigma f^{'}_k \\
&= -\frac{1}{2}\frac{1}{\theta}(1-F_k) + f_k(\frac{1}{2\sigma\theta} - \frac{\sigma}{2\psi})(\frac{k}{2\theta} - \alpha - \frac{\sigma^2}{2\psi}(1-2\theta\alpha)) + \\
&\quad - f_k(\frac{k}{2\theta} + \frac{(1-k)\sigma^2}{2\psi} - \alpha)(\frac{1}{2\sigma\theta} - \frac{\sigma}{2\psi}) \\
&= -\frac{1}{2}\frac{1}{\theta}(1-F_k) + f_k(\frac{1}{2\sigma\theta} - \frac{\sigma}{2\psi})(\frac{(1-k)\sigma^2}{2\psi} - \frac{\sigma^2}{2\psi}(1-2\theta\alpha)) \\
&= -\frac{1}{2}\frac{1}{\theta}(1-F_k) - f_k(\frac{1}{2\sigma\theta} - \frac{\sigma}{2\psi})\frac{\sigma^2}{2\psi}(k-2\theta\alpha)
\end{aligned} \tag{39}$$

noting that $(1-F_k) > 0$ and that $k - 2\alpha\theta) > 0$, it derives that a sufficient condition for (37) to be negative is that $(\frac{1}{2\sigma\theta} - \frac{\sigma}{2\psi}) > 0$, or that $\theta < \frac{\psi}{\sigma^2}$, which in turn means that $a^{cg} > \sigma d^{cg}$, proving the result. Following the same line of reasoning and recalling Proposition 2, it is simple to show that

$$\frac{\partial}{\partial k}\big(\mathbb{E}[\mathcal{U}^f_{cg}(k)|\beta(k|\mathcal{K})] - \mathcal{U}^f_v\big) \leq 0 \tag{40}$$

is never verified for $k \in [0, 2\alpha\theta]$, meaning that only corner solutions are possible.

Trade-off between contingent and non-contingent green debt contracts. The co-existence of the two green debt contracts is explained by the trade-off between the opportunity cost of commitment associated with the non-contingent contract g and the distortion discount associated with the outcome-based contingent contract cg. Section 1.5.4 makes use of a synthetic *project based contingent green contract pcg*, which embeds both ex-ante commitment to actions and ex-post manipulation of outcomes, to separate the two terms of the trade-off as

$$\mathbb{E}[\mathcal{U}^f_{cg}] - \mathcal{U}^f_g = \underbrace{\mathbb{E}[\mathcal{U}^f_{cg}] - \mathcal{U}^f_{pcg}}_{\text{opportunity cost of commitment}} - \underbrace{(\mathcal{U}^f_g - \mathcal{U}^f_{pcg})}_{\text{distortion discount}} \tag{41}$$

The comparative statics outlined in Section 1.5.4 show that the opportunity cost of commitment is roughly independent of the distortion cost parameter ψ (Figure 1.2, right-hand plot), and so latter can be approximated by

$$\mathbb{E}[\mathcal{U}^f_{cg}] - \mathcal{U}^f_{pcg} \approx -(1 - F(\sigma, \alpha, \theta))(\frac{1}{2\theta} - \alpha) + \sigma f(\sigma, \alpha, \theta) \tag{42}$$

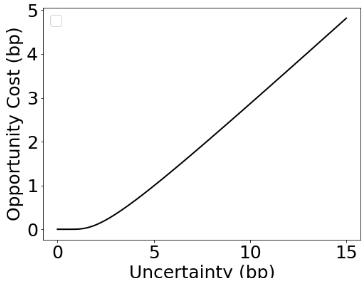
where $F(\sigma, \alpha, \theta) = \mathcal{N}(\frac{1}{\sigma}(\frac{1}{2\theta} - \alpha))$ is the cumulative normal distribution and $f(\sigma, \alpha, \theta) = F^{'}(\sigma, \alpha, \theta)$ is the density function. To calibrate the parameters in (42), it is useful to notice that the *green premium* on the non-contingent contract g, defined as the negative difference between the interest rate on the contract g and the plain vanilla contract v, is given by

$$-(\rho^g - \rho^v) = \mathbb{E}[g(a^g, \tilde{z})] = \frac{1}{\theta} \tag{43}$$

From the expression in (43) one can therefore infer the action cost parameter θ using empirical estimates of the green bond premium. Specifically, the literature finds a green premium that varies between 20 and 30 basis points in the primary market (see Kapraun, Latino, Scheins, and Schlag [2021]) and a smaller green premium of 1 to 9 basis points in the secondary market (see Zerbib [2019] and Flammer [2021]). Assuming that the action cost parameter θ is such that to match an average green premium of 10 basis points and the label cost α is negligible, Figure B.11 reports an upperbound of the opportunity cost of commitment in (42) as a function of the uncertainty σ. Assuming that σ is as large as the expected green outcome in (43) (e.g. equal to 10 basis point green premium), the distortion discount in (41) would therefore need to account for roughly 30% of the green bond premium (e.g. 3 basis points) to make the trade-off comparable. While there is scarce empirical literature that quantifies the effects of greenwashing on the firm's borrowing costs, a recent paper by Attig, Rahaman, and Trabelsi [2021] on bank loans supports our analysis

Figure B.11 *Opportunity cost of commitment*

The plot show the opportunity cost of commitment in (42) as a function of the uncertainty σ when the action cost θ is calibrated to match an average green premium of 10 basis points (bp).



documenting that greenwashing significantly increases the firm's borrowing costs through higher fees and collateral requirements.

Risk-neutrality. In what follows we show that introducing risk-aversion does not alter the baseline prediction of the model.[46] Specifically, assume an otherwise equivalent model with a risk-adverse investor, denote Λ the investor's discount factor, with $\mathbb{E}[\Lambda] = 1$ and $Cov(\Lambda, \tilde{z}) < 0$, then recalling the firm's problem in (1.9), the new investor participation constraint reads

$$\begin{aligned} -b_0^y + \mathbb{E}[\Lambda(b_1^y + x^y g(\tilde{z}, a^y))] &\geq 0 \\ -1 + \mathbb{E}[\Lambda(1 + \rho^y + x^y g(\tilde{z}, a^y))] &\geq 0 \\ \mathbb{E}[\Lambda(\rho^y + x^y g(\tilde{z}, a^y))] &\geq 0 \\ \mathbb{E}[\rho^y + x^y g(\tilde{z}, a^y)] + Cov(\Lambda, \rho^y + x^y g(\tilde{z}, a^y)) &\geq 0 \end{aligned} \tag{44}$$

therefore, taking count of risk-aversion amounts to introducing a covariance term in the participation constraint on the contract-specific rate. Such constrained rate therefore becomes

$$\rho^g \geq -\mathbb{E}[g(\tilde{z}, a^g)] - Cov(\Lambda, g(\tilde{z}, a^g)) \tag{45}$$

for the project-based non-contingent green debt, whereas it becomes

$$\bar{\rho}^{cg} \geq \mathbb{E}[\sigma x^{cg}(\tilde{z}) d^{cg}(\tilde{z})] - Cov(\Lambda, \sigma x^{cg}(\tilde{z}) d^{cg}(\tilde{z})) \tag{46}$$

for the outcome-based contingent contract. Now recalling that $Cov(\Lambda, g(\tilde{z}, a^g)) = Cov(\Lambda, \sigma\tilde{z})$ and

[46] Similarly, one can show that under the current model specification, a risk-adverse firm would have the same utility function across all contract choices.

that $Cov(x^{cg}(\tilde{z})d^{cg}(\tilde{z}), \tilde{z}) \geq 0$, it derives that the new covariance term increases the minimum acceptable rate on both the green debt contracts. Notably though, the magnitude of the covariance term in (46) depends on the level of manipulation in the contract. Specifically in absence of manipulation, the covariance term in (46) disappears and the firm has a further reason to issue the contingent contract, in that by doing so it would avoid the risk-premium required by the investor for holding a contract that delivers an uncertain green outcome. Viceversa if the level of manipulation is high (e.g. the distortion cost ψ is low), then the risk-premium required by the investor for holding the contingent contract would be greater than that required for holding the non-contingent green debt, in turn making this contract less appealing, everything else equal. In summary, introducing risk-aversion does not alter the baseline theoretical prediction outlined in the risk-neutral model.

Certain monetary return and firm capital structure. In the model, we assume that monetary returns are certain and therefore we abstract from any analysis regarding the firm's capital structure and how it relates to the investor's green preferences. We show below that in a simple extension of the model which allows for uncertain monetary returns, equity acts as a perfect substitute to vanilla non-contingent debt, and that high firm types should therefore hold more debt relative to low firm types. Specifically, denote $R(\tilde{\epsilon})$ as the uncertain project cashflow with $\mathbb{E}[R(\tilde{\epsilon})] = \bar{R}$ and $Cov(\tilde{\epsilon}, \tilde{z}) = 0$. Assume that the firm can issue equity at the competitive price $e_0 = \$1 + \bar{R}$ at date $t = 0$ which delivers $e_1 = \$1 + R(\tilde{\epsilon})$ at date $t = 1$, and denote w as the equity ratio of the firm. Then the firm's utility for a given financing choice w, y becomes

$$\mathcal{U}_{y,w} = \max_{a,x} \mathcal{C}^f_{0,y,w} + \mathcal{C}^f_{1,y,w} - xc(a) \tag{47}$$

where

$$\begin{aligned} \mathcal{C}^f_{0,y,w} &= we_0 + (1-w)b^y_0 - 1 = w\bar{R} \\ \mathcal{C}^f_{1,y,w} &= 1 + R(\tilde{\epsilon}) - we_1 - (1-w)b^y_1 = (1-w)(R(\tilde{\epsilon}) - \rho^y) \end{aligned} \tag{48}$$

such that

$$\begin{aligned} -we_0 - (1-w)b^y_0 + \mathbb{E}[(1-w)(b^y_1 + x^y g(\tilde{z}, a^y)) + w(1 + R(\tilde{\epsilon}))] \geq 0 \\ -w\bar{R} + \mathbb{E}[(1-w)(\rho^y + x^y g(\tilde{z}, a^y)) + wR(\tilde{\epsilon})] \geq 0 \\ (1-w)\mathbb{E}[(\rho^y + x^y g(\tilde{z}, a^y))] \geq 0 \end{aligned} \tag{49}$$

substituting budget and participation constraints into the firm's problem, one gets that the expected utility reads

$$\mathbb{E}[\mathcal{U}_{y,w}] = w\bar{R} + (1-w)\mathbb{E}[R(\tilde{\epsilon})] + \mathbb{E}[x^y g(\tilde{z}, a^y)] = \bar{R} + (1-w)\mathbb{E}[x^y g(\tilde{z}, a^y)] \tag{50}$$

from which derives that the firm is indifferent between debt and equity whenever the expected compensation for the green outcome is zero, whereas has a strict preference for debt when the expected compensation for the green outcome is positive.

C CDP Dataset

We employ detailed data on firms' voluntary disclosures from the Carbon Disclosure Project (CDP). CDP sends out environment-related questionnaires to firms each year, and we obtain firms' responses from 2011 to 2017. In total, over 3,000 publicly listed firms from different sectors and countries respond to the questionnaires. We focus on the CDP subsample of publicly listed North American firms that are also in the panel available from the CRSP/COMPUSTAT database between 2010 and 2016.[47] We find a total of roughly 700 CDP firms which match with the selected CRSP/COMPUSTAT sample,[48] but not all matched firms report all variables necessary for our analysis, and some provide inconsistent disclosures. As detailed below, we clean raw disclosures of climate risks, carbon emissions, and emissions reduction targets in order to get firm-level metrics of beliefs, actions, and plans that survive internal consistency checks, and can be validated against external data. The final dataset (consisting of 449 unique firms that report carbon emissions and regulation risk for *at least* two consecutive years) is reported in the third column of Table C.8 below.

[47] We keep only firms in the CRSP/COMPUSTAT North America (Fundamental Annual) dataset with non-missing Tickers within the 2010–2016 accounting period. We lag the information from CRSP/COMPUSTAT by one year to account for a time window between the filling and the final release of the CDP questionnaires.

[48] Matches are computed at the Ticker level.

Table C.8 *Selected Disclosures*

Number of firms in the CRSP/COMPUSTAT North America universe reporting selected disclosures in the CDP questionnaires between 2011 and 2017. Column (1) is the subset of firms that disclose climate risk (regulation); column (2) is the number of firms that disclose total carbon footprint; column (1)+(2) is the selected dataset: firms that disclose carbon risk, carbon footprint, and report to the dataset for at least two consecutive years. Column (3) is the subset of firms in the selected sample that also disclose emissions reduction plans in the previous reporting year.

	(1)	(2)	(1)+(2)	(3)
Reporting Year	Climate Risk	Footprint	Risk & Footprint	Plans
2011	243	390	**227**	**103**
2012	297	429	**227**	**103**
2013	332	465	**277**	**118**
2014	342	468	**291**	**135**
2015	372	481	**326**	**144**
2016	402	508	**340**	**160**
2017	418	505	**368**	**178**
Total Firms	526	611	449	256

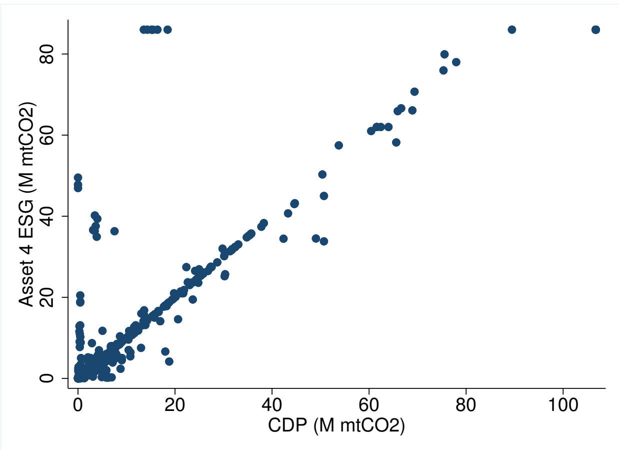
Emissions. Raw disclosures of carbon emissions are from CDP data worksheets that pertain to emissions data. For each firm i and reporting year t, we compute emissions as

$$Emissions_{i,t} = Scope1_{i,t} + Scope2_{i,t} \tag{51}$$

Where $Scope1$ denotes direct emissions (e.g. for 2017 we look at the sheet "CC8. Emissions Data") and $Scope2$ denotes indirect emissions (e.g. for 2017 we look at the sheet "CC83a. Emissions Data"). In each reporting year, firms can provide multiple estimates of direct or indirect emissions, i.e., there are different vintages of the data. To avoid overlapping disclosures in the time-series, we select only disclosures of carbon emissions related to the latest accounting year: this can either be one year prior to, or the same year as, the reporting year, depending on the date of submission of the firm's data.

Figure C.8 *Emissions*

The scatter plot shows firm-level values of CO_2 emissions from Asset 4ESG (y-axis) against self-reported CO_2 emissions from CDP, winsorized between the 1^{st} and the 99^{th} percentile of the pooled distribution. Asset 4 ESG emissions refer to the variable ENERDP023 (see the Asset 4 ESG Dada Glossary for details). The matched sample refers to the entire reporting period in the dataset.



Beliefs. Raw disclosures of regulation risk are from CDP sheets related to climate change risks driven by regulation (e.g. for 2017 we look at the sheet "CC5.1a" on risks driven by changes in regulation). Firms' descriptions of the regulation risk they face vary across firms and reporting years in the dataset. The word cloud below highlights some of the most frequent words that appear in the unstructured text field in the pooled dataset in which firms describe the specific regulation risks. As the figure shows, firms refer to several different types of climate regulation. Firms most frequently stated type of anticipated climate regulation is, as one might expect, fuel energy taxes and carbon taxes, to which follows a cap and trade system. Firms also refer to emissions reporting programmes as a third category of potential climate regulation. These text disclosures partly motivate our modelling choice, described in the paper, of regulation in the form of a carbon levy.

Figure C.8 *Regulation - Description by Firms*

Unlike carbon emissions, risk disclosures always refer to the latest accounting year available. However, firms usually describe multiple types of regulation events as they differentiate, for example, at the plant or business unit levels. For each firm i and reporting year t, we therefore compute the aggregate belief metric as

$$\Lambda_{it} = \sum_{k=0}^{k_{it}} \beta^{H_k - t} M_k q_k \tag{52}$$

where $k = 0, \ldots k_{it}$ varies over the number of events disclosed by firm i in reporting year t, while M_k and q_k are the magnitude and likelihood respectively of each event k. Figure C.8 below summarizes the frequency of disclosures as well as the expected impact of the event $\tilde{\Lambda}_k q_k$ by event horizon H_k.

Figure C.8 *Beliefs - Constituents*

The right plot shows the average expected impact of the regulation event across different maturities of the regulation event. The left plot indicates the frequency of disclosures across each time horizon as collected from the selected CDP sample between 2011 and 2017.

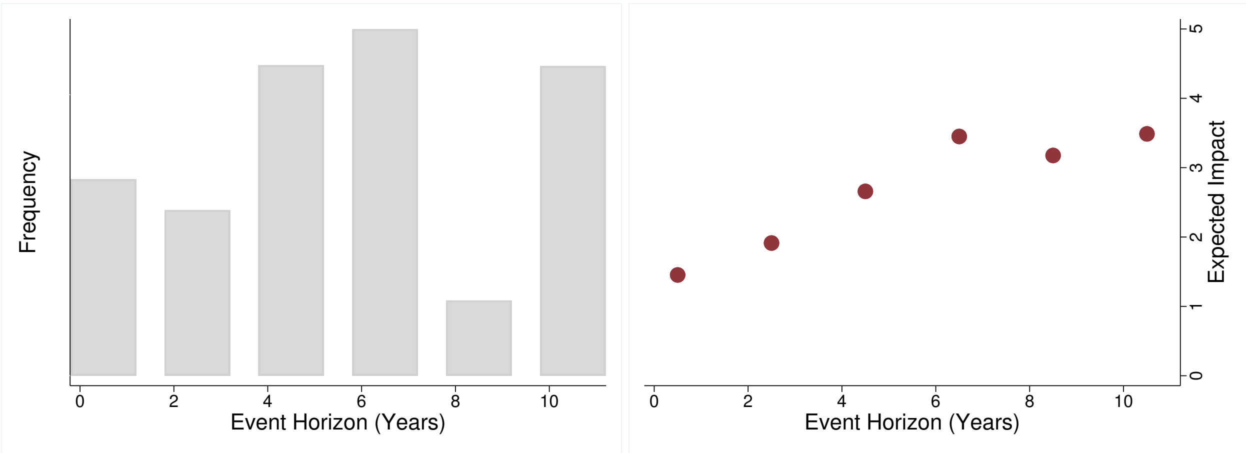


Table C.9 *Beliefs - Linear Regressions*

Linear regressions of beliefs on carbon emissions and market value. Market value is provided by CRSP/COMPUSTAT, carbon emissions are collected from CDP, both the variables are expressed in logarithmic scale. Industry dummies are identified at the GICS industry level, while state dummies are identified at the Head Quarters (HQ) level, both provided by CRSP/COMPUSTAT. Standard errors in square brackets are clustered at the firm-level. *,**,*** indicates statistical significance at the 10%, 5% and 1% level respectively.

Regressor	**Beliefs**			
Emissions	0.17***	0.19***	0.23***	0.16***
	[0.04]	[0.04]	[0.05]	[0.04]
Market Value		-0.13***	-0.11***	-0.13**
		[0.04]	[0.04]	[0.05]
Intercept	0.04	0.69	-0.10	0.52
	[0.54]	[0.57]	[0.62]	[0.37]
Industry dummy?	No	No	Yes	Yes
Year dummy?	No	No	Yes	Yes
HQ State dummy?	No	No	No	Yes
$\mathcal{R}^2$	0.04	0.06	0.10	0.18
Firms	452	452	452	452

Plans. Raw disclosures of emissions reduction targets are from CDP sheets related to targets and initiatives (e.g. for 2017 we look at the sheet "CC3.1a" on absolute emissions reduction targets). As for climate risks, firms can provide multiple targets if they include emissions targets set in previous reporting years that might (or might not) be still active in the current reporting year. For each firm i and reporting year t, we therefore compute the aggregate metric of abatement plans as:

$$plan_{i,t} = \sum_{k=0}^{k_{it}} \frac{1}{T_k - t_k} \sum_{s=t+1}^{T_k} \beta^{s-t} e_k \tag{53}$$

where $k = 0, \ldots k_{it}$ ranges over the total number of targets reported by the firm that are still active in the reporting year t (i.e. $t < T_k$), while $\frac{e_k}{T_k - t_k}$ is the average yearly rate of emissions reduction relative to target k, with $t_k \leq t$ the baseline year of the target. To get rid of inconsistent disclosures, we trim the distribution of the reduction rate e_k so that it lies between $0 \leq e_k \leq 1$. Figure C.9 below summarizes the frequency of disclosures as well as the reduction rate e_k by target horizon T_k.

Figure C.9 *Plans - Constituents*

The right plot shows the average emissions reduction target across different target maturities. The left plot indicates the frequency of disclosures across each time horizon as collected from the selected CDP sample between 2011 and 2017.

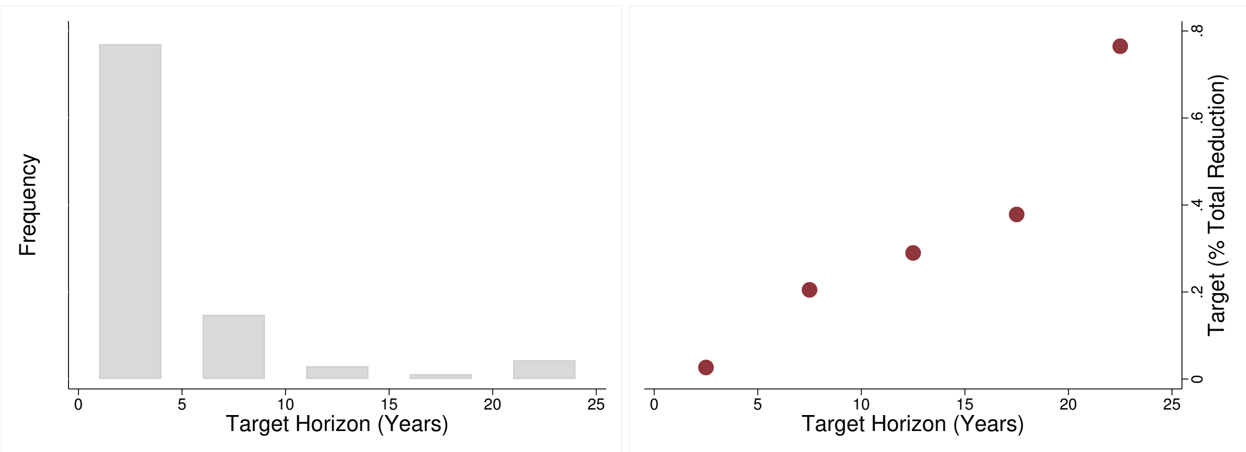
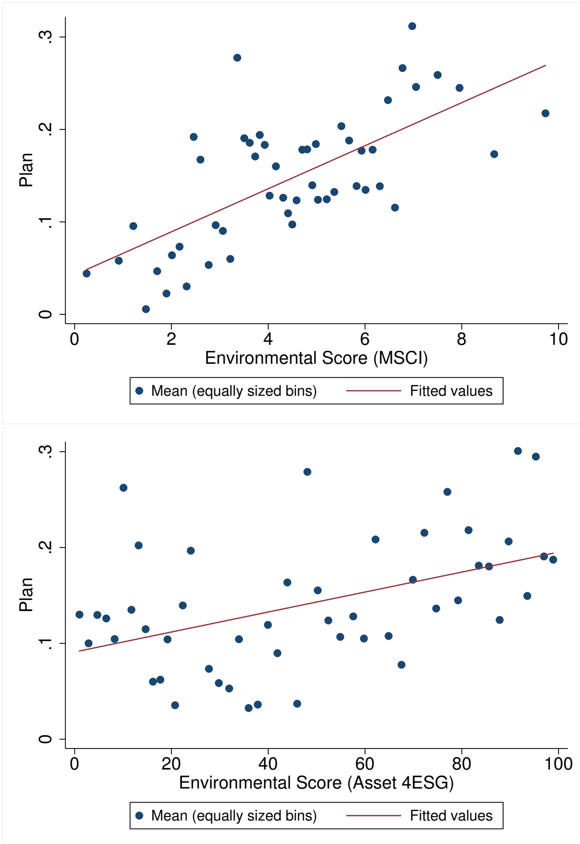


Figure C.9 *Plans - External Environmental Ratings*

The top and bottom plots show abatement plans (y-axis) averaged across equally sized bins of the Environmental score (x-axis) provided by MSCI and Thomson Reuters Asset 4ESG respectively. Environmental scores are constituents of the ESG scores (see the Asset 4 ESG and the MSCI Dada Glossary for details).



Robustness checks

Figure C.9 *Beliefs - Reputation vs Regulation Risk*

The plot compares average time-series dynamics of firms' self-reported beliefs about regulation risk (red line) and reputation risk (blue line) respectively, both normalized by their sample averages. Reputation risk is a subset of the third type of risk reported by firms in CDP, namely risk arising from changes in consumer tastes and social/macroeconomic conditions. The construction of the belief measure follows the same steps as the ones described in the main text.

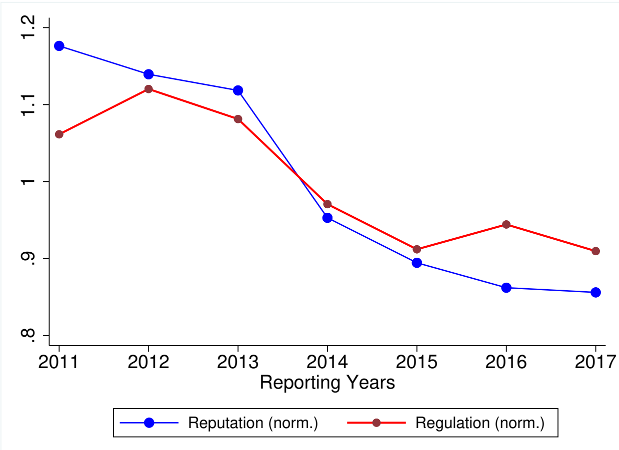
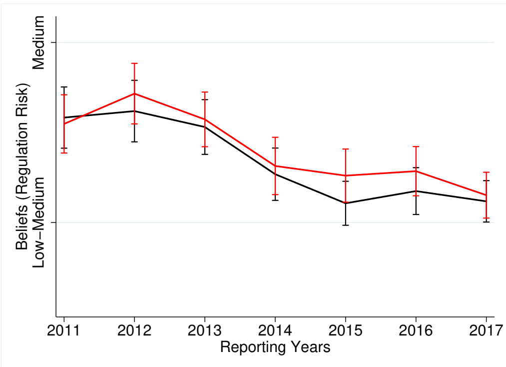
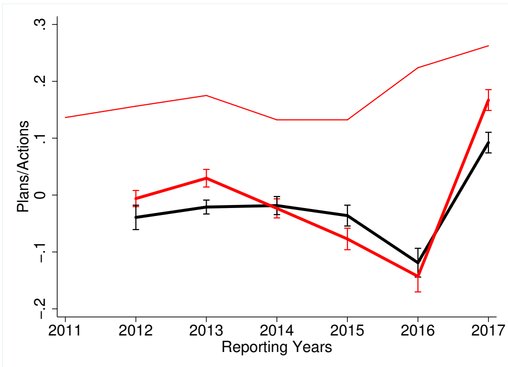


Figure C.9 *Beliefs, Plans, Actions - Restricted Sample*

The left and right-hand plots report beliefs, actions, and plans respectively as constructed from a restricted CDP sample which excludes *unknown* responses from the analysis. Variables are otherwise constructed following the same procedures as the ones reported in the main text.





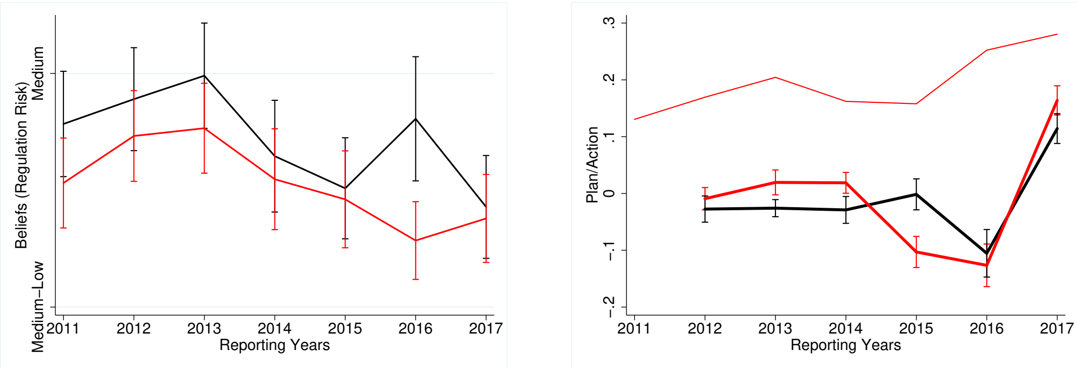
D Model Appendix

Solving the Single Firm Model. The Bellman equation for the single firm problem reads:

$$V_t = \max_{x_t}\{\omega k_t - \frac{1}{2}\phi x_t^2 k_{t-1} + \beta V_{t+1}\} \tag{54}$$

Figure C.9 *Beliefs, Plans, Actions - Balanced Panel*

The left and right-hand plots report beliefs, actions, and plans respectively as constructed from a restricted CDP sample which includes only firms reporting to CDP since 2011. Variables are otherwise constructed following the same procedures as the ones reported in the main text.



where the capital stock satisfies:

$$k_t = k_{t-1}(1 - x_t) \tag{55}$$

Deriving (54) with respect to x_t and using (55), we get:

$$-\omega - \phi x_t = \beta \frac{\partial V_{t+1}}{\partial k_t} \tag{56}$$

Deriving V_{t+1} in (54) with respect to k_t, we then get:

$$\frac{\partial V_{t+1}}{\partial k_t} = \omega(1 - x_{t+1}) - \frac{1}{2}\phi x_{t+1}^2 + \beta \frac{\partial V_{t+2}}{\partial k_{t+1}}(1 - x_{t+1}) \tag{57}$$

where we again used (55). Iterating (56) to get $\partial V_{t+2}/\partial k_{t+1}$ and substituting it into (57), we then get:

$$\frac{\partial V_{t+1}}{\partial k_t} = \omega(1 - x_{t+1}) - \frac{1}{2}\phi x_{t+1}^2 + (-\omega - \phi x_{t+1})(1 - x_{t+1}) \tag{58}$$

which after rearrangement gives:

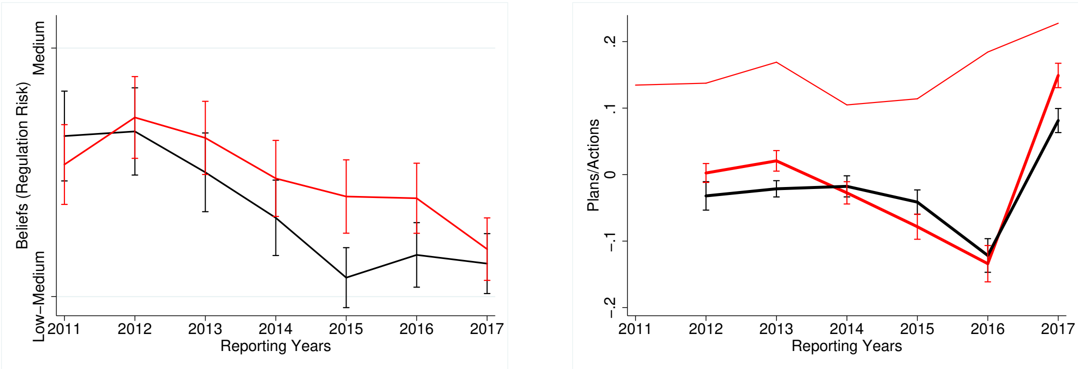
$$\frac{\partial V_{t+1}}{\partial k_t} = \frac{1}{2}\phi x_{t+1}^2 - \phi x_{t+1} \tag{59}$$

now substituting (59) into (56) and solving for x_t, we get:

$$x_t = \beta\Big(x_{t+1} - \frac{1}{2}x_{t+1}^2\Big) - \frac{\omega}{\phi} \tag{60}$$

Figure C.9 *Beliefs, Plans, Actions - Weighted Averages*

The left and right-hand plots report beliefs, actions, and plans respectively as constructed from weighted averages of firms' beliefs, plans, and actions across reporting years. Weights $w_{i,t}$ equal the emission intensity of each firm i in reporting year t, divided by the total emission intensity of firm i's group in reporting year t. Variables are otherwise constructed following the same procedures as the ones reported in the main text.



which proves the result. The expression for the terminal abatement x_T derives directly from the first order condition $\partial \pi_T^\lambda / \partial x_T = 0$, recalling that $\eta_T = \eta k_{T-1}(1 - x_T)$.

Concavity of the abatement rate x_t with respect to λ. We want to show that the inequality

$$\frac{\partial^2 x_t}{\partial \lambda^2} < 0 \tag{61}$$

holds for each maturity $t \in 0, \dots T-1$. Deriving (60) twice with respect to λ, we get:

$$\frac{\partial^2 x_t}{\partial \lambda^2} = \beta \Big(\frac{\partial^2 x_{t+1}}{\partial \lambda^2}(1 - x_{t+1}) - \big(\frac{\partial x_{t+1}}{\partial \lambda}\big)^2 \Big), \tag{62}$$

let us start with $t = T-1$. Recalling the expression for the terminal abatement rate $x_T = \frac{\eta\lambda}{\phi} - \frac{\omega}{\phi}$, we get:

$$\frac{\partial^2 x_{T-1}}{\partial \lambda^2} = -\beta \big(\frac{\partial x_T}{\partial \lambda}\big)^2 = -\beta \big(\frac{\eta}{\phi}\big)^2 < 0, \tag{63}$$

which proves the result. Let us now assume that (61) is true for a certain $t = k$. Then, from (62) we have:

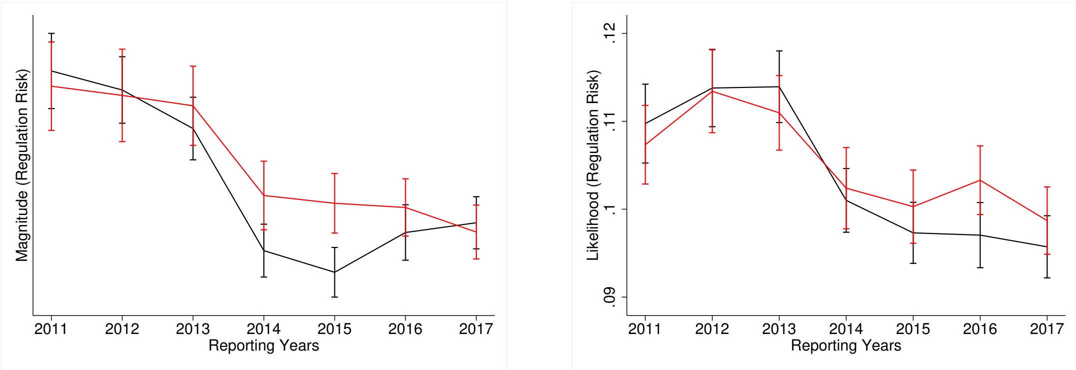
$$\frac{\partial^2 x_{k-1}}{\partial \lambda^2} = \beta \Big(\frac{\partial^2 x_k}{\partial \lambda^2}(1 - x_k) - \big(\frac{\partial x_k}{\partial \lambda}\big)^2 \Big) < \beta \Big(\frac{\partial^2 x_k}{\partial \lambda^2}(1 - x_k) \Big), \tag{64}$$

that is,

$$\frac{\partial^2 x_{k-1}}{\partial \lambda^2} < 0 \quad \longleftrightarrow \quad x_k < 1, \tag{65}$$

Figure C.9 *Beliefs - Magnitude/Likelihood Components*

The left-hand plot reports the average magnitude of the regulation risk across reporting years in CDP. The right-hand plot reports the average likelihood of the regulation risk across reporting years in CDP. The red (black) line refers to firms that disclose (do not disclose) plans in the previous reporting year.



which falls in the range of admissible solutions for x_k.

Leader-Follower Model

Assumption of asymmetric information. In our theoretical framework, the firm that reports plans for future abatement is designated as more informed about the climate policy than the firm that does not report plans. This provides us a rationale for the derivation of the leader-follower equilibrium. This section outlines evidence in favour of this modelling assumption, which is ultimately motivated in the text as a way to rationalize the observed differences in beliefs across the two types of firms.

Table 1 and Figure 2 in Section 3 of the paper summarize differences in characteristics across firms that report and do not report plans for emissions reduction in CDP. As discussed, firms that report plans are overrepresented in the utility sector, which is the sector targeted the most by climate regulation. These firms also have higher market value, more assets, higher income, and lower cost of capital. Using a stakeholder framework, Artiach et al. [2010] suggest a number of hypotheses that relate firms' financial performance to their decisions to invest in corporate sustainability. One hypothesis is that in times of low profitability, firms with high debt will be forced to prioritize financial over societal stakeholders. This makes it more likely that firms with lower leverage and higher income have higher performance along the sustainability or environmental dimension. A second hypothesis is that as firms' financial characteristics also influence their ability to participate in costly sustainability programmes, it is likely that larger firms with lower cost of

Figure C.9 *Actions - Distribution*

The plot shows the distribution of percentage changes in total (e.g. Scope 1 + Scope 2) emissions across reporting years in CDP, winsorized between the 5^{th} and the 95^{th} percentile of the pooled sample.

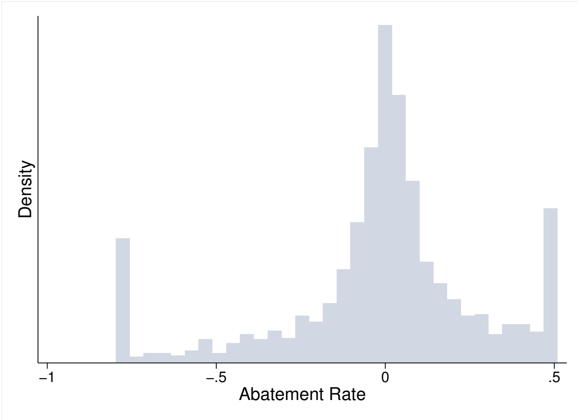
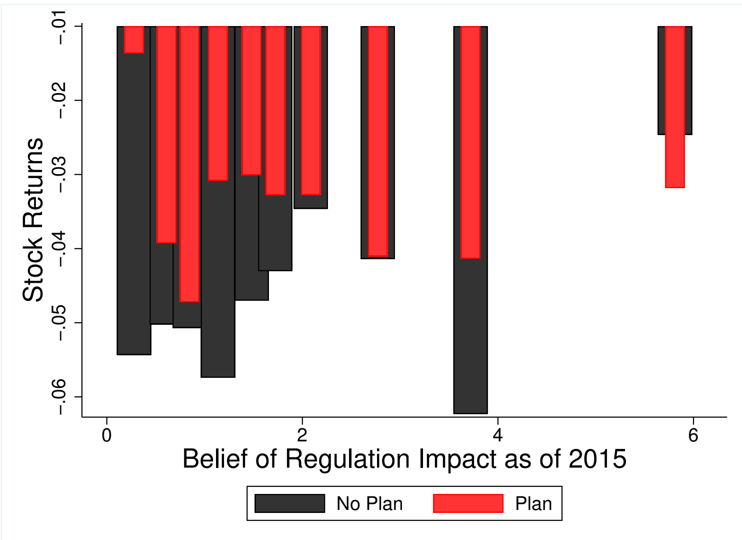


Figure C.9 *Stock Reaction around Paris Agreement*

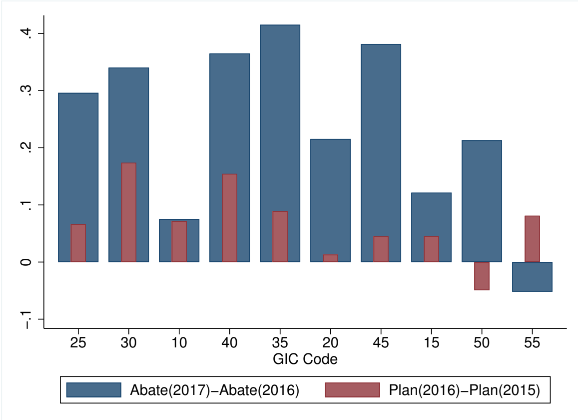
The plot shows average stock returns around the announcement of the Paris Agreement (Saturday, 12^{th} December of 2015) against equally-sized bins of beliefs relative to the reporting year 2015. Stock returns are relative changes in stock prices (between the last working day preceding the announcement and the first working day following the announcement) as collected from CRSP. The red (black) bars refer to firms in the selected CDP dataset that disclose (do not disclose) targets in the previous reporting year.



capital have higher sustainability performance. To the extent that firms with higher propensity to invest in corporate sustainability also manage environmental risks more carefully, it is then likely that their information over these risks is more precise than the other firms in the dataset.

Figure C.9 *Revisions in Plans and Actions across Industries*

The bar plot shows average changes in reported plans and actions across GICS industries. The red bars refer to changes in plans between the years surrounding the Paris agreement announcement. The blue bars refer to changes in actions between the years surrounding the Paris agreement.



The statistics reported in Table D.10 provide more direct support to our assumption, showing that firms that report plans for future emissions abatement are more likely to engage with policymakers and more likely to be involved in lobbying for climate regulation—by providing direct funding to support these activities. Engagement with policymakers, which often constitutes an important dimension of firms' engagement in corporate sustainability, can often provide more direct access to valuable information about future climate regulation (see Ovtchinnikov et al. [2019], Zhang et al. [2019] and Heitz et al. [2019] respectively).

Table D.10 *Active participation to regulatory policy*

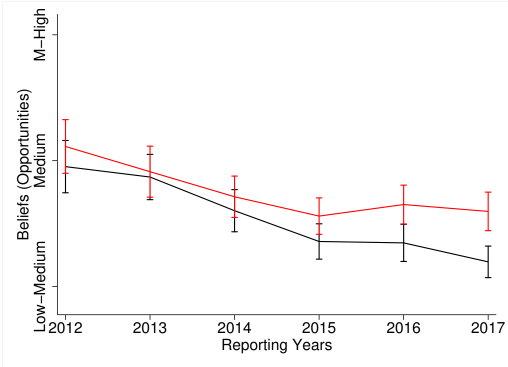
Percentage of firms that engage with policymakers and provide fundings to climate regulatory activities as collected from CDP disclosures in 2017. The first (second) column refers to the group of firms that disclose (do not disclose respectively) plans in the previous reporting year.

	Plan	**No Plan**
Engage with policymakers	94%	78%
Provide direct funding	72%	53%
Total Firms	157	208

Solving the leader-follower model. The Bellman equation for the leader-follower model reads:

Figure C.9 *Beliefs - Climate Change Opportunities*

The plot reports average beliefs about climate change opportunities across the three broad types of risks against reporting years in CDP. The red (black) line refer to firms in the selected CDP dataset that disclose (do not disclose) targets in the previous reporting year. The beliefs metric is constructed following the same procedure as the ones reported in the main text.



$$V_t^l = \max_{x_t^l} \{\omega k_t^l - \frac{1}{2}\phi(x_t^l)^2 k_{t-1}^l + \gamma_t x_t^f x_t^l k_{t-1}^l + \beta V_{t+1}^l\} \tag{66}$$

and:

$$V_t^f = \max_{x_t^f} \{\omega k_t^f - \frac{1}{2}\phi(x_t^f)^2 k_{t-1}^f + \gamma_t x_t^l x_t^f k_{t-1}^f + \beta V_{t+1}^f\} \tag{67}$$

Taking x_t^l as given, x_t^f is first derived following the same steps as in the baseline case with no externalities. It is then simple to show that the optimal abatement rate of the follower satisfies:

$$x_t^f = w_t x_t^l + f_{t+1} \tag{68}$$

with $w_t = \frac{\gamma_t}{\phi}$ and f_{t+1} given by:

$$f_{t+1} = \beta\Big(x_{t+1}^f - w_{t+1}x_{t+1}^l - \frac{1}{2}(x_{t+1}^f)^2\Big) - \frac{\omega}{\phi} \tag{69}$$

Now substituting (68) into (66), the leader's Bellman equation reads:

$$V_t^l = \max_{x_t^l} \{\omega k_t^l - \frac{1}{2}\phi(x_t^l)^2 k_t^l + \gamma_t(w_t x_t^l + f_{t+1}) x_t^l k_{t-1}^l + \beta V_{t+1}^l\} \tag{70}$$

From the first order conditions with respect to x_t^l, one gets:

$$-\omega - \phi x_t^l + \gamma_t(2w_t x_t^l + f_{t+1}) = \beta \frac{\partial V_{t+1}^l}{\partial k_t^l} \tag{71}$$

Recalling that $w_t = \frac{\gamma_t}{\phi}$, we rewrite the expression in (71) as:

$$-\omega - \phi(1 - 2w_t^2)x_t^l + \phi w_t f_{t+1} = \beta \frac{\partial V_{t+1}^l}{\partial k_t^l} \tag{72}$$

Following the same procedure as in (57) and (58), we get:

$$\begin{aligned} \frac{\partial V_{t+1}^l}{\partial k_t^l} &= \omega(1 - x_{t+1}^l) - \frac{1}{2}\phi(x_{t+1}^l)^2 + \gamma_{t+1} x_{t+1}^f x_{t+1}^l \dots \\ \dots &+ (1 - x_{t+1}^l)\Big[-\omega - \phi x_{t+1}^l + \gamma_{t+1}(x_{t+1}^f + w_{t+1} x_{t+1}^l)\Big] \end{aligned} \tag{73}$$

where we used (68) to rewrite $\gamma_{t+1}(2w_{t+1}x_{t+1}^l + f_{t+2}) = \gamma_{t+1}(x_{t+1}^f + w_{t+1}x_{t+1}^l)$. After rearrangement, this gives:

$$\frac{\partial V_{t+1}^l}{\partial k_t^l} = \frac{1}{2}\phi(1 - 2w_{t+1}^2)(x_{t+1}^l)^2 - \phi(1 - w_{t+1}^2)x_{t+1}^l + \gamma_{t+1} x_{t+1}^f \tag{74}$$

Putting (74) back into (72) and solving for x_t^l, we finally get:

$$x_t^l = \frac{w_t}{(1 - 2w_t^2)} f_{t+1} + \beta\Big(\frac{(1 - w_{t+1}^2)x_{t+1}^l - w_{t+1}x_{t+1}^f}{1 - 2w_t^2} - \frac{(1 - 2w_{t+1}^2)}{(1 - 2w_t^2)2}(x_{t+1}^l)^2\Big) - \frac{\omega}{\phi(1 - 2w_t^2)} \tag{75}$$

which by substituting the expression for f_{t+1} in (75) gives us the result.
The terminal abatement x_T^l is determined from the first order condition $\partial \pi_T^l / \partial x_T^l = 0$, with:

$$\pi_T^l = \omega k_T^l - \frac{1}{2}\phi(x_T^l)^2 k_{T-1}^l + \gamma_T x_T^f(x_T^l) x_T^l k_{T-1}^l - (\bar{\lambda} + \tilde{s})\eta_T \tag{76}$$

where the follower's terminal abatement given the leader's reads:

$$x_T^f(x_T^l) = w_T x_T^l + \frac{\eta}{\phi}(\bar{\lambda}) - \frac{\omega}{\phi} \tag{77}$$

deriving the expression in (76) with respect to x_T^l and solving for x_T^l, we get:

$$x_T^l = \frac{\eta}{\phi}\Big(\bar{\lambda}\frac{1 + w_T}{1 - 2w_T^2} + \tilde{s}\frac{1}{1 - 2w_T^2}\Big) - \frac{\omega}{\phi}\frac{1 + w_T}{1 - 2w_T^2} \tag{78}$$

from which one we also get x_T^f by substituting the expression (78) into (77).

Proof of the Proposition. From the explicit expression in (78) we get:

$$\frac{\partial x_T^l}{\partial \bar{\lambda}} = \frac{\eta}{\phi}\frac{1+w_T}{1-2w_T^2} \tag{79}$$

and substituting the expression (78) into (77) and deriving x_T^f with respect to $\bar{\lambda}$ we get:

$$\frac{\partial x_T^f}{\partial \bar{\lambda}} = \frac{\eta}{\phi}\big(1 + w_T\frac{1+w_T}{1-2w_T^2}\big) = \frac{\eta}{\phi}\frac{1+w_T-w_T^2}{1-2w_T^2} \tag{80}$$

from which we immediately get:

$$\frac{\partial x_T^l}{\partial \bar{\lambda}} > \frac{\partial x_T^f}{\partial \bar{\lambda}} \quad \forall \quad w_T \neq 0, |w_T| \leq \frac{1}{\sqrt{2}} \tag{81}$$

which recalling that $\gamma_T = \phi w_T$ proves the result.

Proof of the Corollary. Recalling the expression for the terminal abatement rate of the single-firm model, we get:

$$\frac{\partial x_T^l}{\partial \bar{\lambda}} > \frac{\partial x_T}{\partial \bar{\lambda}} \quad \longleftrightarrow \frac{1+w_T}{1-2w_T^2} > 1 \tag{82}$$

and similarly:

$$\frac{\partial x_T^f}{\partial \bar{\lambda}} > \frac{\partial x_T}{\partial \bar{\lambda}} \quad \longleftrightarrow \frac{1+w_T-w_T^2}{1-2w_T^2} > 1 \tag{83}$$

which are both satisfied for $w_T > 0$, $w_T < \frac{1}{\sqrt{2}}$. By induction, it is also possible to show that the result holds for shorter maturities $t < T$ provided the set of model parameters $\{\phi, \beta, \mu, \omega, \bar{\lambda}, \tilde{s}\}$ is such that the optimal abatement rates $x_{t+1}^f|_{\bar{\lambda}}, x_{t+1}^l|_{\bar{\lambda}} < 0$, and the payoff externality $\gamma_t > 0$, $\gamma_t' < 0$. Consider the case of the leader. Assume $\frac{\partial x_{t+1}^l}{\partial \bar{\lambda}} > \frac{\partial x_{t+1}}{\partial \bar{\lambda}}$ for $t+1$. Deriving (75) with respect to the parameter $\bar{\lambda}$, we get:

$$\begin{aligned}\frac{\partial x_t^l}{\partial \bar{\lambda}} = \frac{\beta}{1-2w_t^2}\Big[&\frac{\partial x_{t+1}^l}{\partial \bar{\lambda}}(1-w_{t+1}^2-w_t w_{t+1}) + \frac{\partial x_{t+1}^f}{\partial \bar{\lambda}}(w_t - w_{t+1})\dots \\ &\dots - \Big(\frac{\partial x_{t+1}^l}{\partial \bar{\lambda}}(1-w_{t+1}^2)x_{t+1}^l + \frac{\partial x_{t+1}^f}{\partial \bar{\lambda}} w_t x_{t+1}^f\Big)\Big]\end{aligned} \tag{84}$$

Provided that $w_t \geq w_{t+1}$, we get after some computation:

$$\frac{\partial x_t^l}{\partial \bar{\lambda}} > \beta\Big(\frac{\partial x_{t+1}^l}{\partial \bar{\lambda}}(1-x_{t+1}^l) - \frac{\partial x_{t+1}^f}{\partial \bar{\lambda}} w_t x_{t+1}^f)\Big) \tag{85}$$

from which the result follows, recalling that $\frac{\partial x_{t+1}^l}{\partial \bar{\lambda}} > \frac{\partial x_t^l}{\partial \bar{\lambda}}$, $x_{t+1}^l < 0$, $x_{t+1}^f < 0$, and $w_t > 0$.

Supplementary Results to the Leader-Follower Model

Proposition. *For each maturity $t < T$, discount rate β, adjustment cost ϕ and size of the reputation externalities $\gamma_t, \gamma_{t+1} \in (0, \frac{\phi}{\sqrt{2}})$ that verify the following inequality*

$$\gamma_{t+1} \leq \gamma_t \sqrt{1 + 4(\frac{\phi^4(1-1/\beta)}{\gamma_t} + \frac{2\phi^2\gamma_t}{\beta})} \tag{86}$$

there exists a set of model parameters $\{\mu, \omega, \bar{\lambda}, \rho, \tilde{s}\}$ that invert the optimal profile of abatement for the leader firm, that is $x^l_t > x^l_{t+1} > 0$.

Proof. The expression in (75) can be put in compact notation as

$$x^l_t = x^l_{t+1} b_{t,t+1} - a_{t,t+1}(x^l_{t+1})^2 - c_{t,t+1} \tag{87}$$

where the coefficient of the linear term is $b_{t,t+1} = \beta\frac{(1-w^2_{t+1}-w_t w_{t+1})}{1-2w^2_t}$, the coefficient of the quadratic term is $a_{t,t+1} = \beta\frac{1}{2}\frac{1-2w^2_{t+1}}{1-2w^2_t}$ and the coefficient of the constant term is $c_{t,t+1} = \frac{\omega}{\phi(1-2w^2_t)} - \frac{x^f_{t+1}(w_t-\beta w_{t+1}-w_t x^f_{t+1})}{(1-2w^2_t)}$. We therefore have that

$$x^l_t > x^l_{t+1} \iff (b_{t,t+1}-1)x^l_{t+1} - a_{t,t+1}(x^l_{t+1})^2 - c_{t,t+1} > 0 \tag{88}$$

which holds whenever x^l_{t+1} falls in the range

$$x^l_{t+1} \in \Big[b_{t,t+1} - 1 - \frac{\sqrt{(b_{t,t+1}-1)^2 - 4a_{t,t+1}c_{t,t+1}}}{2a_{t,t+1}}, b_{t,t+1} - 1 + \frac{\sqrt{(b_{t,t+1}-1)^2 - 4a_{t,t+1}c_{t,t+1}}}{2a_{t,t+1}}\Big] \tag{89}$$

A sufficient condition for the upperbound

$$b_{t,t+1} - 1 + \frac{\sqrt{(b_{t,t+1}-1)^2 - 4a_{t,t+1}c_{t,t+1}}}{2a_{t,t+1}} \tag{90}$$

to be strictly positive, which in turns implies an inverted order of abatement $x^l_t > x^l_{t+1} > 0$, is that $b_{t,t+1} > 1$. This in turn requires that w_t and w_{t+1} satisfy

$$\frac{(1-w^2_{t+1}-w_t w_{t+1})}{1-2w^2_t} > \frac{1}{\beta} \tag{91}$$

which solving for $\gamma_t, \gamma_{t+1} \in (0, \frac{\phi}{\sqrt{2}})$ proves the result.

Calibration and Alternative Setup

In Section 3, when performing the calibration of the baseline model, we specify the dynamics of beliefs λ_t in input as a non-linear transformation of the dynamics of beliefs Λ_t of the representative firm in the dataset, to account for the fact that the latter are extracted from categorical disclosures, and that the firms are learning across reporting periods in the dataset. Specifically, we assume that each observed revision in beliefs is a function of a *regularized* signal $\sigma\big(\tilde{x}_t\big)$ and a time-varying weight m_t, that is

$$\Lambda_t - \Lambda_{t-1} = m_t \ \sigma\big(\tilde{x}_t\big) \tag{92}$$

This specification corrects for the fact that, even if signals $\tilde{x}_t$ are unbounded, firms' disclosures are constrained to fixed categories. The choice $m_t = 1/t$ is a shortcut from Bayesian learning from normally distributed signals[49]. To extract the original signal, we then invert the sigmoid function to get

$$\tilde{x}_t = \sigma^{-1}\big(\frac{\Lambda_t - \Lambda_{t-1}}{m_t}\big) \tag{93}$$

where in particular $\sigma(x) = \frac{2\Delta}{1+e^{-x}} - \Delta$, with $\Delta = \max_t |\Lambda_t - \Lambda_{t-1}|$ the largest revision in reported beliefs in absolute terms, so that $\sigma(x) \in (-\Delta, +\Delta)$ for $x \in (-\infty, +\infty)$.

To conclude the analysis, we show how our calibration results performed in Section 4 change in the case where firms endogenize the payoff externality induced by reputation in a simultaneous equilibrium setting, assuming heterogeneous adjustment costs and heterogeneous beliefs over the levy. Specifically, we relax the assumption of asymmetric information across firms, assuming instead that firms are simply endowed with heterogeneous beliefs over the levy. Relaxing this assumption in turn implies that the leader firm has no commitment power over the follower firm, which results in a simultaneous equilibrium where firms act based on their expectations over the competitor's action (and therefore their expectations over the competitor's belief). It is simple to show that the terminal abatement rates in this setting read:

[49] Assuming a signal $\tilde{x} = \theta + \tilde{\epsilon}$ is received at each time t, with ρ_ϵ the precision of the signal and ρ_0 the precision of the prior θ_0. Then for each time t the precision of the prior is $\rho_t = \rho_0 + (t-1)\rho_\epsilon$, and the weight assigned to the signal is $m_t = \rho_\epsilon/(\rho_0 + (t-1)\rho_\epsilon)$. Assuming $\rho_\epsilon = \rho_0$, then $m_t = 1/t$

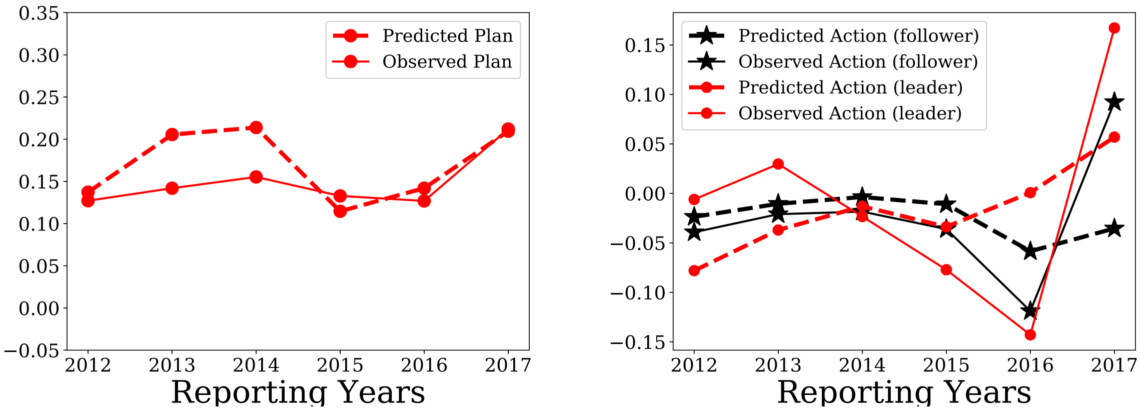
$$x_T^i = \frac{\eta}{\phi_i}\left(\lambda_i \frac{1+w_{iT}}{(1-w_{iT}^2)}\right) - \frac{\omega(1+w_{iT})}{\phi_i(1-w_{iT}^2)} \tag{94}$$

where we let the adjustment cost parameter ϕ_i vary across firms with and without plans to capture fundamental differences across firms with and without plans in the data.

This expression can be compared with the expressions in (78) and (77). Specifically, each firm now amplifies in a symmetric manner the sensitivity of the abatement rate x_T^i with respect to its own belief over the levy, λ_i. However, as we let the adjustment cost ϕ_i vary across firms, the sensitivity parameters $\frac{\eta}{\phi_i}\frac{1+w_{iT}}{(1-w_{iT}^2)}$ will also vary across firms. Figure D.10 reports the results of the calibration outlined in Section 3 under the assumption that firms follow the simultaneous game described above. As observed, keeping the hypothesis of the reputation externality allows us to capture variation in the predicted abatement rates, which is an improvement relative to the baseline setting with no externalities. However, by relaxing the assumption of asymmetric information we fail to capture an extra degree of correlation between firms' abatement actions: in particular, firms with plans are predicted to begin reducing emissions one year ahead of firms without plans, reflecting only the dynamics of their own beliefs over the levy. This is not what we observe in the data.

Figure D.10 *Model Implied and Observed Moments*

The left plot compares the model-implied and observed (lagged) abatement plan across reporting years in CDP. The right plot compares the model-implied and observed abatement actions across reporting years in CDP. Thick (dashed) lines refer to observed (model-implied) moments, red-circle (black-star) lines refer to the subset of firms with (without) abatement plans respectively. Input parameters are $\beta = 0.93$, $T = 10$, $\omega = 0.19$, $\bar{\lambda} = 2.70$, $\phi_l = 27.0$, $\phi_f = 22.4$, $\eta = 1$, $\gamma = 24.4$, $g = 0.63$.



E Out of Sample Predictions

To conduct our out-of-sample validation exercise, we extend the CDP dataset to include U.S. public firms' responses from 2018 and 2019. Over these two years, CDP implemented a set of changes to make the questionnaires more aligned with the recommendations of the Task Force on Climate-Related Financial Disclosures (TCFD), established in 2016. Below, we describe the major changes to the dataset arising as a result of these changes, as well as adjustments that we implemented to our construction of the data as a result of these changes to make the out-of-sample data consistent with our treatment of the in-sample data.

First, regulation risk in the later period is part of a broader classification of climate-related risks, collectively labelled "climate transition risks". These risks include: marked shifts in consumer tastes, reputation risks from negative stakeholder feedback, technology risk due to forced substitution of products and services, and policy risk from new or existing regulations. To preserve continuity with the previous setting, we select firms' disclosures related only to this policy risk component. Second, time horizons of climate-related risks are not tied to numeric ranges as in the earlier data. That is, firms in the later period of the data choose from options: current, short-term, medium-term, and long-term horizons. To preserve continuity with the previous setting, we therefore translate these responses into the time ranges provided by CDP before 2018. More specifically, current horizon is translated into 0 to 1 years from the time of reporting, short-term horizon to 1 to 3 years from reporting, medium-term horizon to 3 to 6 years from reporting, and long-term horizon to beyond 6 years from reporting. Finally, while responses have remained unaltered as far as emissions reduction targets and total carbon emissions are concerned, a number of firms reporting CDP questionnaires in 2018 and 2019 have taken the option to hide their emissions data. As a consequence, of the 368 firms reporting emissions and risks in 2017 (see Table 1), only 137 report emissions in the consecutive year, and 73 of these also report targets. We focus on the data for this reduced number of firms in our out-of-sample exercise.

Figure E.10 *Regulation - Description by Firms*

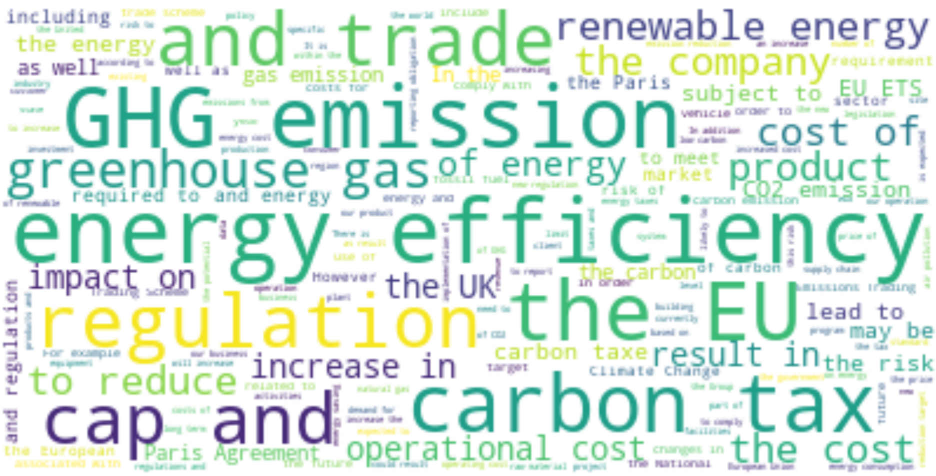
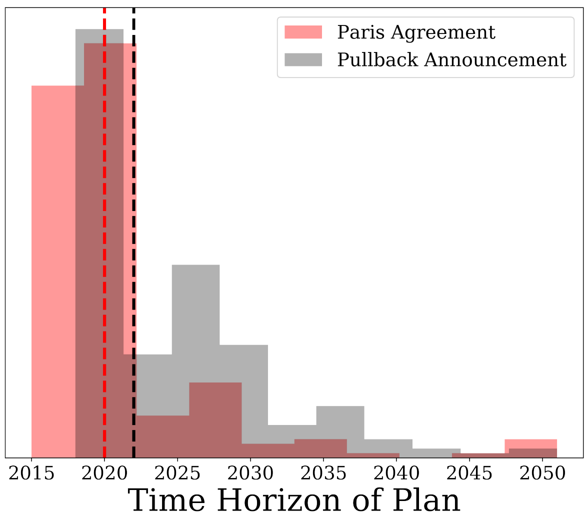


Figure E.10 *Time Horizon of Emissions Reduction Targets*

The histogram shows the distribution of time horizons for planned emissions reduction as reported by firms with plans in the dataset. The red bars refer to time horizons as reported in the year following the Paris agreement announcement, while black bars refer to time horizons as reported in the year following the President Trump's pullback announcement.



F Model Appendix

Proposition 1. The regulator aims to choose the combination $\{\tau_i, \bar{\delta}_i\}_{i=1,...n}$ so that to minimize the aggregate loss

$$\mathcal{L} = \mathbb{E}[\sum_{i=1}^{n}(1 - r_i^*(\tau_i, \bar{\delta}_i))(C^*(\tau_i) + ae_i^*(\tau_i)) + r_i^*(\tau_i, \bar{\delta}_i)(ae_i^o + \tilde{x}_i^s)] \tag{95}$$

subject to the constraint

$$\sum_{i=1}^{n} ae_i(\bar{\delta}_i) \leq D \tag{96}$$

if $\tilde{x}_i = +\infty$ for each i, then optimal relocation is necessarily $r_i^*(\tau_i, \bar{\delta}_i) = 0$ for each target choice $\bar{\delta}_i$. The regulator's loss in (98) is therefore only a function of the carbon tax choice τ_i. The budget constraint in (96) is redundant and can be optimally verified by setting $\{\bar{\delta}_i\}_i = 1$. The first order condition with respect to τ_i yields

$$\begin{aligned} \frac{dC^*(\tau_i^*)}{d\tau_i} + a\frac{de_i^*(\tau_i^*)}{d\tau_i} &= 0 \\ -\tau_i^*\frac{de_i^*(\tau_i^*)}{d\tau_i} + a\frac{de_i^*(\tau_i^*)}{d\tau_i} &= 0 \quad \text{iff} \quad \tau_i^* = a \end{aligned} \tag{97}$$

where the second equality follows from the firm's Euler condition with respect to optimal abatement $\frac{dC^*(\tau_i)}{d\tau_i} = -\tau_i\frac{de^*(\tau_i)}{d\tau_i}$.

Proposition 2. I first solve for the optimal tax τ_i for a given target $\bar{\delta}_i$, and then solve for the optimal target that satisfies the budget constraint. The lagrangian of the regulator problem reads

$$\mathcal{L} = \sum_{i=1}^{n} C^*(\tau_i) + ae_i^*(\tau_i) + \sum_{i=1}^{n}\mathbb{E}[r_i^*(\tau_i, \bar{\delta}_i)(ae_i^o + \tilde{x}_i^s - C^*(\tau_i) - ae_i^*(\tau_i))] + \lambda(\sum_{i=1}^{n} ae_i(\bar{\delta}_i) - D) \tag{98}$$

Recalling the explicit expression for the firm's optimal relocation choice, the partial derivative of the second term with respect to τ_i reads

$$\begin{aligned} &\frac{\partial}{\partial\tau_i}\mathbb{E}[1\{\tilde{x}_i \leq C^*(\tau_i) + \tau_i e_i^*(\tau_i)\}(ae_i^o + \tilde{x}_i^s - C^*(\tau_i) - ae_i^*(\tau_i))] \\ =&\frac{\partial}{\partial\tau_i}\Big((ae_i^o + f_i + \bar{x}_i - C^*(\tau_i) - ae_i^*(\tau_i))\Phi(C^*(\tau_i) + \tau_i e_i^*(\tau_i)) + \sigma_i\frac{\phi_i(C^*(\tau_i) + \tau_i e_i^*(\tau_i))}{\Phi_i(C^*(\tau_i) + \tau_i e_i^*(\tau_i))}\Big) \\ =&(\tau_i - a)\Phi_i(C^*(\tau_i) + \tau_i e_i^*(\tau_i))\frac{de_i^*(\tau_i^*)}{d\tau_i} \end{aligned} \tag{99}$$

with Φ_i and ϕ_i denoting firm i's cumulative normal distribution function and density function respectively, where the last equality follows from the properties of the truncated normal distribution and the fact that $\frac{dC^*(\tau_i)}{d\tau_i} = -\tau_i \frac{de^*(\tau_i)}{d\tau_i}$. The first order condition with respect to the carbon tax τ_i therefore reads

$$(-\tau_i^* + a)\frac{de_i^*(\tau_i^*)}{d\tau_i} + \frac{\partial}{\partial \tau_i}\mathbb{E}[1\{\tilde{x}_i \leq C^*(\tau_i) + \tau_i e_i^*(\tau_i)\}(ae_i^o + \tilde{x}_i^s - C^*(\tau_i) - ae_i^*(\tau_i))] = 0$$
$$(-\tau_i^* + a)\frac{de_i^*(\tau_i^*)}{d\tau_i}(1 - \Phi_i(C^*(\tau_i) + \tau_i e_i^*(\tau_i))) = 0 \quad \text{iff} \quad \tau_i^* = a \tag{100}$$

which proves the first result. For a given tax choice $\tau_i = a$, the first condition with respect to the target $\bar{\delta}_i$ then reads

$$\begin{aligned} &\frac{\partial}{\partial \bar{\delta}_i}\mathbb{E}[r_i^*(a, \bar{\delta}_i^*)v_i(a)] = \lambda a e_{i0} \\ &\frac{\partial}{\partial \bar{\delta}_i}\mathbb{E}[r_i^*(\tau_i, \bar{\delta}_i^*)\frac{v_i(a)}{ae_{i0}}] = \lambda \end{aligned} \tag{101}$$

from which the result follows noting that $w_i(a) = \frac{v_i(a)}{e_{i0}}$ and $v_i(a) = (ae_i^o + \tilde{x}_i^s - C^*(a) - ae_i^*(a))$.

Proposition 3. Denote $\hat{\delta}_i$ a constraint-feasible target allocation and define an intermediate allocation

$$\bar{\delta}_i(b) = (1-b)\bar{\delta}_i^* + b\hat{\delta}_i \tag{102}$$

for b a weight that varies between 0 and 1. Denote the difference in welfare loss as a function of the weight b as

$$\Delta\mathcal{L}(b) = \sum_{i=1}^{n} \mathcal{L}(\{\bar{\delta}_i(b)\}) - \mathcal{L}^* \tag{103}$$

with $\mathcal{L}^*$ the constrained minimum in (98) and $\mathcal{L}(\{\bar{\delta}_i(b)\})$ the welfare evaluated in the constrain-feasible targets. Denote for simplicity $r_i^*(\bar{\delta}_i(b)) = r_i^*(a, \bar{\delta}_i(b))$ and $w_i = w_i(a)$, differentiate the expression in (103) by b obtaining

$$\frac{d\Delta\mathcal{L}(b)}{db} = \sum_i e_{i0}\frac{\partial \mathbb{E}[r_i^*(\bar{\delta}_i(b))w_i]}{\partial \bar{\delta}_i}\frac{\partial \bar{\delta}_i(b)}{\partial b} - \lambda \sum_i e_{i0}\frac{\partial \bar{\delta}_i(b)}{\partial b} = \sum_i e_{i0}\frac{\partial \mathbb{E}[r_i^*(\bar{\delta}_i(b))w_i]}{\partial \bar{\delta}_i}(\hat{\delta}_i - \bar{\delta}_i^*) \tag{104}$$

where the lagrangian term disappears as $\bar{\delta}_i(\rho)$ moves between two feasible targets and hence $\sum_{i=1}^n e_{i0}(\hat{\delta}_i - \bar{\delta}_i^*) = 0$. Apply a first-order Taylor approximation in $b = 0$ to get

$$\begin{aligned}
\frac{d\Delta\mathcal{L}(b)}{db} &\approx \sum_i e_{i0}\big[\frac{\partial\mathbb{E}[r_i^*(\bar{\delta}_i^*)w_i]}{\partial\bar{\delta}_i} + \frac{\partial^2\mathbb{E}[r_i^*(\bar{\delta}_i^*)w_i]}{\partial\bar{\delta}_i^2}(\bar{\delta}_i - \delta_i^*)\big](\hat{\delta}_i - \bar{\delta}_i^*) \\
&\approx \sum_i e_{i0}\big[\lambda + \frac{\partial^2\mathbb{E}[r_i^*(\bar{\delta}_i^*)w_i]}{\partial\bar{\delta}_i^2}((1-b)\bar{\delta}_i^* + b\hat{\delta}_i - \delta_i^*)\big](\hat{\delta}_i - \bar{\delta}_i^*) \\
&\approx b\sum_i e_{i0}\frac{\partial^2\mathbb{E}[r_i^*(\bar{\delta}_i^*)w_i]}{\partial\bar{\delta}_i^2}(\hat{\delta}_i - \bar{\delta}_i^*)^2
\end{aligned} \tag{105}$$

which gives the result once again noting that $\sum_i e_{i0}(\hat{\delta}_i - \bar{\delta}_i^*) = 0$. Finally, integrate the marginal loss between $b = 0$ and $b = 1$ to get

$$\Delta\mathcal{L} = \int_0^1 \frac{d\Delta\mathcal{L}(b)}{db}db = \frac{1}{2}\sum_i e_{i0}\frac{\partial^2\mathbb{E}[r_i^*(\bar{\delta}_i^*)w_i]}{\partial\bar{\delta}_i^2}(\hat{\delta}_i - \bar{\delta}_i^*)^2 \tag{106}$$

which proves the result.

Exit threshold. The explicit expression for firm i's operating profits read

$$\pi_i^o(\delta) = py_i^o - se_{i0}(1-\delta) - \frac{1}{2}\psi(e_{i0})(\delta - \theta_i)^2 \tag{107}$$

the abatement rate δ_i^o that achieves the unconstrained maximum profits satisfies

$$\begin{aligned}
\frac{d\pi_i^o(\delta_i^o)}{d\delta} &= 0 \\
-se_{i0} + \psi(e_{i0})(\delta - \theta_i) = 0 \text{ iff } &\text{ iff } \quad \delta_i^o = \frac{e_{i0}}{\psi(e_{i0})}s + \theta_i
\end{aligned} \tag{108}$$

recalling the definition of the emissions abatement cost, for a given δ one has

$$C_i(\delta) = \pi_i^o(\delta_i^o) - \pi_i^o(\delta) = se_{i0}(\delta_i^o - \delta) + \frac{1}{2}\psi(e_{i0})((\delta - \theta_i)^2 - (\delta_i^o - \theta_i)^2) \tag{109}$$

the abatement rate δ_i^* that minimize compliance costs with the regulation satisfies

$$\begin{aligned}
\frac{dC_i(\delta_i^*)}{d\delta} - ae_{i0} &= 0 \\
-se_{i0} + \psi(e_{i0})(\delta - \theta_i) - ae_{i0} = 0 \text{ iff } &\quad \delta_i^* = \frac{e_{i0}}{\psi(e_{i0})}(s + a) + \theta_i = \delta_i^o + \frac{e_{i0}}{\psi(e_{i0})}a
\end{aligned} \tag{110}$$

from which follows that

$$C_i^* = -sa\frac{e_{i0}^2}{\psi(e_{i0})} + \frac{1}{2}\frac{e_{i0}^2}{\psi(e_{i0})}(a^2 + 2as) = \frac{1}{2}\frac{e_{i0}^2}{\psi(e_{i0})}a^2 \tag{111}$$

plugging this into the optimal relocation choice, one has

$$\begin{aligned}
r_i^* &= 1\{C_i^* + ae_{i0}(\bar{\delta}_i - \delta_i^*) \geq \tilde{x}_i\} \\
&= 1\{\bar{\delta}_i \geq \delta_i^* - \frac{C_i^*}{ae_{i0}} + \frac{\tilde{x}_i}{ae_{i0}}\} \\
&= 1\{\bar{\delta}_i \geq \theta_i + \frac{e_{i0}}{\psi(e_{i0})}(s+a) - \frac{C_i^*}{ae_{i0}} + \frac{\tilde{x}_i}{ae_{i0}}\} \\
&= 1\{\bar{\delta}_i \geq \theta_i + \frac{e_{i0}}{\psi(e_{i0})}(s+1/2a) + \frac{\tilde{x}_i}{ae_{i0}}\} \\
&= 1\{\bar{\delta}_i \geq \tilde{z}_i\}
\end{aligned} \tag{112}$$

which proves the result.

Corollary 1. Under the baseline assumption that $v_i \approx k_{0i}$ and recalling (112), the Euler condition for the targets in (101) is given by

$$\begin{aligned}
\frac{\partial}{\partial\bar{\delta}_i}\mathbb{E}[1\{\tilde{z}_i \leq \bar{\delta}_i\}\frac{k_{i0}}{e_{i0}}] &= \lambda \\
\frac{\partial}{\partial\bar{\delta}_i}\Phi(\frac{\bar{\delta}_i - \mathbb{E}[\tilde{z}_i]}{\sigma_i}) &= \frac{\lambda}{w_i} \\
\frac{1}{\sigma_i}\phi(\frac{\bar{\delta}_i - \mathbb{E}[\tilde{z}_i]}{\sigma_i}) &= \frac{\lambda}{w_i}
\end{aligned} \tag{113}$$

with Φ and cumulative normal distribution and ϕ normal density respectively. Expliciting and applying the logarithm on both sides, one gets

$$\frac{1}{2}(\frac{\bar{\delta}_i - \mathbb{E}[\tilde{z}_i]}{\sigma_i})^2 + log(\sqrt{2\pi}\sigma_i\frac{\lambda}{w_i}) = 0 \tag{114}$$

which solving for $\bar{\delta}_i$ gives

$$\bar{\delta}_i = \mathbb{E}[\tilde{z}_i] - \sigma_i^2\sqrt{-2log(\sqrt{2\pi}\sigma_i\frac{\lambda}{w_i})} \tag{115}$$

which proves the result.

Corollary 2. To compute the welfare loss I use the expression in (106) adapted for the current setting. The welfare loss is determined by the square difference between the two optimal target $_i^*$ in (115) and the type-specific target $\bar{\delta}_i^*(\theta_i)$ where the type θ_i enters the expected exit threshold and the total uncertainty $\sigma_{xi} < \sigma_i$. The second derivative of the relocation propensity evaluated in the optimal targets reads

$$\begin{aligned}\frac{\partial^2}{\partial\bar{\delta}_i^2}\Phi(\frac{\bar{\delta}_i^*-\mathbb{E}[\tilde{z}_i]}{\sigma_i}) &= -(\frac{\bar{\delta}_i^*-\mathbb{E}[\tilde{z}_i]}{\sigma_i})\frac{1}{\sigma_i}\phi(\frac{\bar{\delta}_i^*-\mathbb{E}[\tilde{z}_i]}{\sigma_i})\frac{1}{\sigma_i}\\ &= \frac{\lambda}{w_i}\sqrt{-2log(\sqrt{2\pi}\sigma_i\frac{\lambda}{w_i})}\frac{1}{\sigma_i}\end{aligned} \tag{116}$$

where the second equality is obtained by substituting the expression for $\bar{\delta}_i^*$ in (115). On the other hand, it is possible to show that the squared difference between the type-sensible target and the one in (113) is simply given by[50]

$$\mathbb{E}[(\bar{\delta}_i^*-\hat{\delta}_i)^2] = \mathbb{E}[\theta_i^2] = \sigma_\theta^2 \tag{117}$$

So the welfare loss takes the explicit expression

$$\begin{aligned}\Delta\mathcal{L}^* &= \frac{1}{2}\sum_i e_{i0}w_i\frac{\partial^2}{\partial\bar{\delta}_i^2}\Phi(\frac{\bar{\delta}_i^*-\mathbb{E}[\tilde{z}_i]}{\sigma_i})\mathbb{E}[(\bar{\delta}_i^*-\hat{\delta}_i)^2]\\ &= \frac{1}{2}\frac{\sigma_\theta^2}{\sigma_i}\sum_i \lambda e_{i0}\sqrt{-2log(\sqrt{2\pi}\sigma_i\frac{\lambda}{w_i})}\end{aligned} \tag{118}$$

which proves the result.

G Data Appendix

I obtain data from the Climate Change Agreement dataset. The CCAs dataset contains in total 5,313 existing or dead target units, of which 453 (8.5%) with multiple facilities. Each target unit is associated to a firm, identified by the UK registered number. Large firms can own multiple target units depending on the output of their facilities. I exclude from the dataset target units that are created after the termination of the first target period, as well as existing target units linked to firms the strategically close those units to open new ones in more favourable industry groups, obtaining a total of 4,080 target units. I match this sample with the Bureau Van Dick (BVD) database between 2012 and 2016 using the UK registered number. I ask that firms in the merged sample report at least their total assets in BVD in 2012. Finally, I drop sectors if they contain less than 5 target units. This leaves me with 2,232 target units associated to 1,961 unique

[50] This comes from the law of large numbers and the fact that both the targets are constraint-feasible.

firms in 37 industry sectors. The selected universe of UK manifacturing firms outside of CCAs are those ones in the ABS database that are selected for the survey and report a non-null payment of the climate levy in 2012. That is, a total of 7,332 unique firms.

Figure G.10 *Largest participants*

The figure shows the cumulative distribution of the largest 20 firms in CCAs by total assets as of 2012. Data are collected from the Bureau Van Dick (BVD) database.

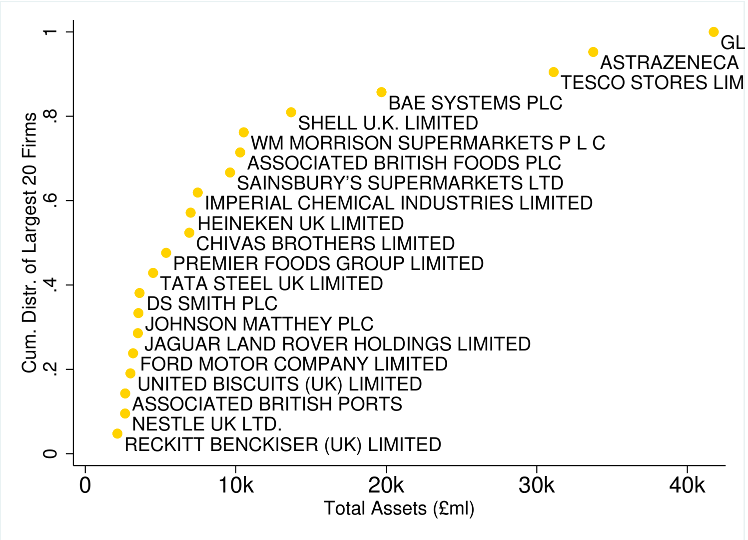
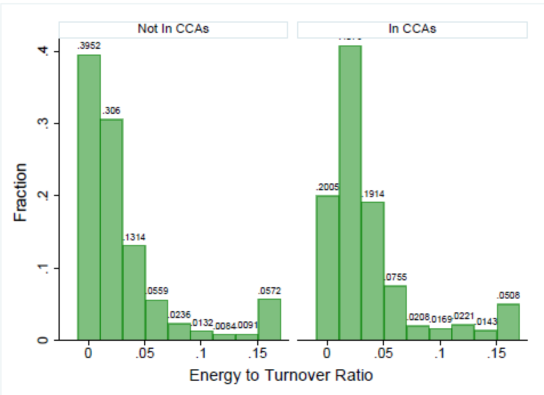
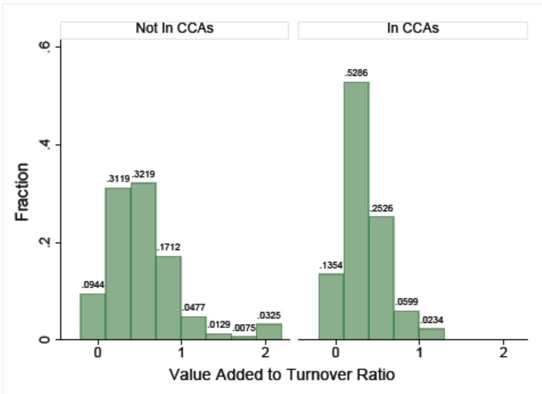


Figure G.10 *Energy and Trade Intensity by inclusion in CCAs*

The left plot shows the distribution of energy intensity for firms outside of the CCAs subject to the CCL (left histogram) and firms in CCAs (right histogram). Energy intensity is computed as total purchased energy divided by turnover as of 2012. The right plot shows the distribution of trade intensity for firms outside of the CCAs subject to the CCL (left histogram) and firms in CCAs (right histogram). Trade intensity is computed as value added divided by turnover as of 2012.





Measuring the carbon-implied cost of the CCL. The estimation of the CCL-implied cost of carbon follows three steps. First of all, I collect energy consumption data at the fossil-fuel source level to the determine average fossil-fuel energy mix of regulated firms, meaning the relative proportion of coal, gasoil, electricity, and natural gas consumed by firms that pay the CCL. Second, for each fossil-fuel source, I convert the CCL from £/Kwh to £/mtCO_2e using relative conversion factors. Therefore, I compute the CCL-implied cost of carbon (as well as the fossil fuel-implied cost of carbon) as the sum of the CCL price in £/mtCO_2e (energy price in £/mtCO_2e respectively) across fossil-fuel sources weighted by the relative proportion of each source in the energy mix.

Source-level energy consumption data are collected from the Quarterly Fuel Inquiry database, a quarterly panel survey directed to a representative set of roughly 500 industrial consumers, containing information about purchased volume and value of gas, electricity, gasoil, coal, and heavy fuel oil. The QFI dataset is available for each quarter until 2014. For the purpose of the analysis, I use data relative to 2012. The consumption data are available in KWh for Electricity and Natural Gas, whereas they are available on tonnes for Heavy Fuel Oil, Gasoil, and Coal. I compute the fossil-fuel energy mix at the 2-digit SIC level as the relative percentage of each fossil-fuel source consumed in that year.

For the conversion factors, I take as a reference the estimates provided by BEIS. When different types of fuels are provided, I take averages within each of the four categories. For UK electricity, the conversion factor is 0.23314 kt CO_2e generated for each unit of KWh consumed. For Coal, it is 0.23314 kt CO_2e generated for each unit of KWh consumed. For Fuel Oil, it is 0.25163 kt CO_2e generated for each unit of KWh consumed. For Natural Gas, it is 0.18387 kt CO_2e generated for each unit of KWh consumed. Energy prices relative to 2012 are taken from BEIS. Levy prices between 2012 and 2016 are taken from the gov.uk website.

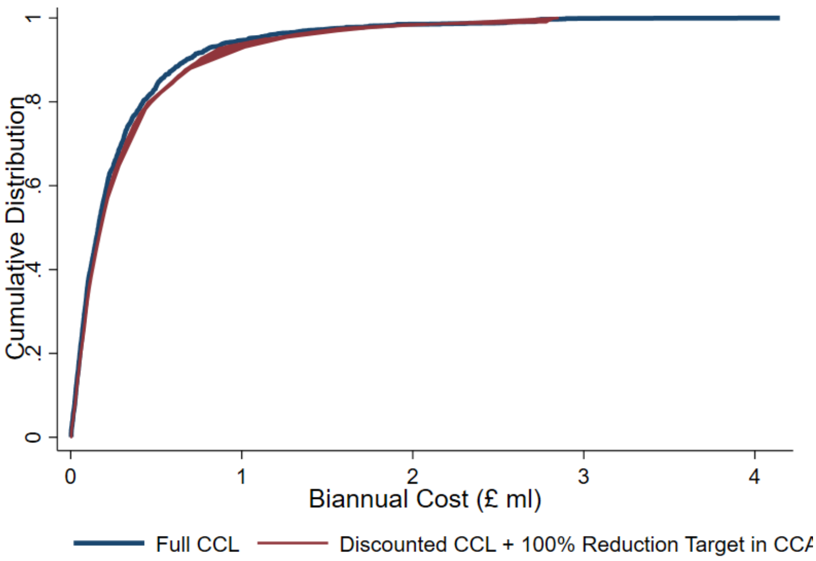
Table G.11 *CCAs Questionnaire*

The table reports the proportion of positive responses, across subsamples of the respondent firms grouped by industry-level energy and trade intensity, to each of the selected questions in the CCAs questionnaire. The CCAs questionaire is relative to the three bi-annual target periods of the second CCAs legislation (e.g. between 2013 and 2019), and is publicly available at *www.gov.uk*. The selected questions are, in order of appearance: Q1 *Energy-intensive business activities that existed at the time you joined the second CCA scheme, and only those covered by the second CCA scheme, that are: ceased entirely/been relocated/neither.*, Q2 *What you take into consideration when you make capital investment in energy efficiency measures?*, Q3 *On how many sites have you done any of the following since April 2013? (a) Energy efficiency (b) Replacement of process equipment (c) Change in fuel*, Q4 *How important were the following factors in your decision to participate to CCAs? (a) The reduction in CCL (b) The cost of carbon permit if targets were not met (c) Demonstrating green credentials.*

Q 1	Ceased entirely	Been relocated	Neither		
Energy/Trade intensive	8.3	11.3	83.6		
Non Energy/Trade Intensive	9.0	5.5	88.0		
Q 2	Energy Prices	CCL Rates	External Finance	Payback Horizon	Contribution to CCAs
Energy/Trade intensive	70.3	54.1	78.6	93.1	92.0
Non Energy/Trade Intensive	62.9	45.0	70.1	95.0	82.7
Q 3a	None of the Facilities	Some Facilities	All Facilities		
Energy/Trade intensive	20.1	32.6	47.3		
Non Energy/Trade Intensive	20.1	25.4	59.6		
Q 3b	None of the Facilities	Some Facilities	All Facilities		
Energy/Trade intensive	26.6	27.4	46.0		
Non Energy/Trade Intensive	31.9	19.3	46.2		
Q 3c	None of the Facilities	Some Facilities	All Facilities		
Energy/Trade intensive	76.4	11.6	10.3		
Non Energy/Trade Intensive	73.1	8.2	17.3		
Q 4a	Very Low/Low	Medium	High/Very High		
Energy/Trade intensive	3.4	11.2	85.4		
Non Energy/Trade Intensive	4.0	15.0	81.0		
Q 4b	Very Low/Low	Medium	High/Very High		
Energy/Trade intensive	25.8	28.8	45.6		
Non Energy/Trade Intensive	25.5	30.7	43.7		
Q 4c	Very Low/Low	Medium	High/Very High		
Energy/Trade intensive	16.7	17.6	65.7		
Non Energy/Trade Intensive	24.0	21.5	54.5		

Figure G.10 *Compliance cost*

The plot shows the cumulative distribution of the cost of compliance with the CCL (blue line) and the cost of compliance with the CCAs under a 100% reduction target (red line) assuming an infinite emissions abatement cost. That is for each firm in the dataset, the cost of compliance across the two regulations is measured by multiplying the cost of carbon implied by the CCL (the carbon permit price in CCAs respectively) by the firm's historical emissions as reported in the CCAs.



Variable Selection. The following variables are used in the regression analysis as well as in the quantitative analysis.

- **Emissions intensity.** Historical emissions intensity is computed as

$$\text{Emission Intensity}_{i,j} = \ln(\text{Emissions}_{i,jh}) - \ln(\text{Assets}_{i,j,h}) \tag{119}$$

where $\text{Emissions}_{i,jh}$ (kt CO_2e) are firm-level emissions covered by the CCAs in the previous biannual target period, e.g. between April 2011 and March 2013, and $\text{Assets}_{i,j,h}$ (£m) are total assets in 2012. The variable is winsorized between the 5th and the 95th percentiles of the pooled distribution (Figure G.11).

- **Internal Finance**. The external finance indicator is computed as

$$\text{Internal Finance}_{i,j} = \ln(\text{Credit Limit}_{i,j,h}) - \ln(\text{Turnover}_{i,j,h}) \tag{120}$$

where $\text{Turnover}_{i,j,h}$ (£m) is turnover in 2012 and $\text{Credit Limit}_{i,j,h}$ (£m) is the variable credit limits available from BvD. The variable refers to the maximum amount of flexible (e.g. immediate) credit a financial institution extends to a firm. It can be intended as a proxy for the firm's availability of internal finance/cost of access to external finance. The variable is winsorized between the 5th and the 95th percentiles of the pooled distribution (Figure G.11).

- **Trade Intensity**. Historical trade intensity is computed as

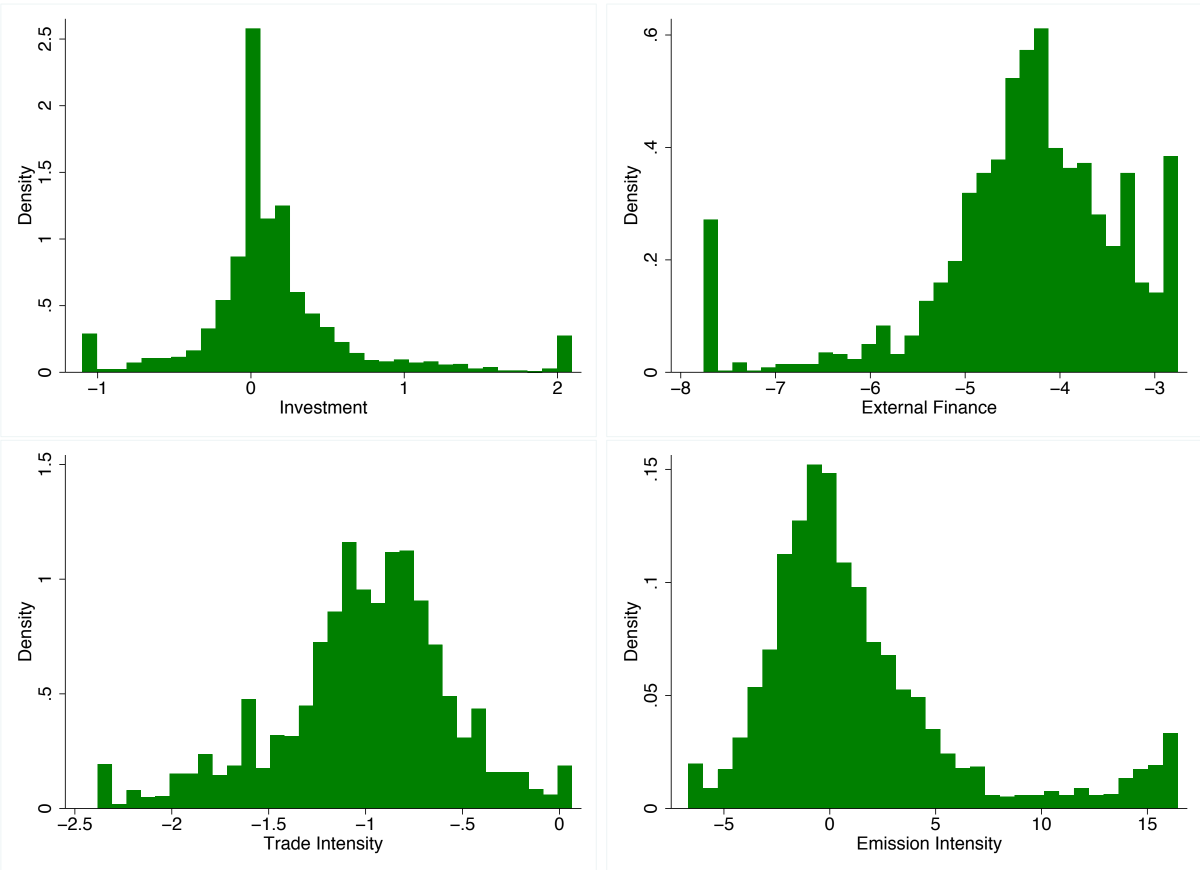
$$\text{Trade Intensity}_{i,j} = \ln(\text{Value Added}_{i,j,h}) - \ln(\text{Turnover}_{i,j,h}) \tag{121}$$

where $\text{Value Added}_{i,j,h}$ (£m) is turnover net of material inputs in 2012, where material input is sourced both domestically and throughout international trade. The variable is winsorized between the 1th and the 99th percentiles of the pooled distribution (Figure G.11).

- **Indirect Carbon Prices**. Indirect carbon prices s_j are computed as detailed above at the 2-digit sector level and include fossil-fuel implied price of carbon augmented of the discounted CCL-implied price of carbon, expressed in £/ $mtCO_2$e.

- **Target**. Emissions reduction targets $\hat{\delta}_j$ are obtained directly from sector-level targets in CCAs and refer to the targets relative to the first target period between 2013 and 2015.

Figure G.11 *Input Variables - Distributions*



Maximum Likelihood Estimation. The parameters in the two-stage estimations are determined such that the log likelihood of participation and conditional performance is maximized.

- **Probit Stage 1.** Denote Θ_1 as the set of parameters to be estimated from first stage, then the model-implied probability of participation is

$$\Pr\{y_{ij} = 1\} = \Phi(f_{ij}(\Theta_1)) \tag{122}$$

where $f_{ij}(\Theta_1) = \frac{1}{\sigma_1}(\mathbb{E}[\tilde{z}_{ij}(\gamma, \beta)] - \bar{\delta}_j) = exp[\tilde{\gamma}^T \psi_{ij}](s_j + 0.5a) + \tilde{\beta}^T[z_{ij}; \bar{\delta}_j]$ and Φ is the cumulative normal distribution function. Then the log likelihood reads

$$\mathcal{L}_1(\Theta_1) = \sum_{i=1}^{n} \big(y_{ij}\ \ln\Phi(f_{ij}(\Theta_1)) + (1 - y_{ij})\ \ln(1 - \Phi(f_{ij}(\Theta_1)))\big) \tag{123}$$

where y_{ij} is the dummy variable equal to 1 if the firm participate in CCAs, specified as in the empirical section, and $\Theta_1 = \{\tilde{\gamma}, \tilde{\beta}\}$. Now denote $q_{ij} = 2y_{ij} - 1$, then is simple to show that the log likelihood above can be expressed as

$$\mathcal{L}_1(\Theta_1) = \sum_{i=1}^{n} \ln\Phi(q_{ij} f_{ij}(\Theta_1)) \tag{124}$$

the parameters Θ_1 that maximize the log likelihood are found by the Newton-Raphson method. Hence it is necessary to compute the gradient (score) and hessian of the log likelihood with respect to Θ_1. This is computed as

$$\nabla_{\Theta_1}\mathcal{L}_1(\Theta_1) = \sum_{i=1}^{n} \frac{\phi(q_{ij} f_{ij}(\Theta_1)) q_{ij}}{\Phi(q_{ij} f_{ij}(\Theta_1))} \nabla_{\Theta_1} f_{ij}(\Theta_1) = \sum_{i=1}^{n} \Lambda_{ij}(\Theta_1) q_{ij} \nabla_{\Theta_1} f_{ij}(\Theta_1) \tag{125}$$

where $\Lambda_{ij}(\Theta_1)$ is the inverse Mill's ratio and $\nabla_{\tilde{\beta}} f_{ij}(\Theta_1) = [z_{ij}; \bar{\delta}_j]$ and $\nabla_{\tilde{\gamma}} f_{ij}(\Theta_1) = exp[\tilde{\gamma}^T \psi_{ij}](s_j + 0.5a)[\psi_{ij}]$. The Hessian reads

$$\Delta_{\Theta_1}\mathcal{L}_1(\Theta_1) = \sum_{i=1}^{n} -q_{ij}\Lambda_{ij}(\Theta_1)(q_{ij}\Lambda_{ij}(\Theta_1) + q_{ij} f_{ij}(\Theta_1))\nabla^T_{\Theta_1} f_{ij}(\Theta_1)\nabla_{\Theta_1} f_{ij}(\Theta_1) + \Lambda_{ij}(\Theta_1) q_{ij} \Delta_{\Theta_1} f_{ij}(\Theta_1) \tag{126}$$

where the hessian $\Delta_{\Theta_1} f_{ij}(\Theta_1) = exp[\tilde{\gamma}^T \psi_{ij}](s_j + 0.5a)[\psi^T_{ij}\psi_{ij}]$. Once obtaining the estimates for $\hat{\Theta}_1$, I retrieve from the inverse of the coefficient on the target $\hat{\sigma}_1 = 1/\tilde{\beta}_{\bar{\delta}}$, hence $\hat{\beta} = \tilde{\beta}\sigma_1$ and $\hat{\gamma}_0 = \tilde{\gamma}_0 + ln\hat{\sigma}_1$, which in turn allows to compute the expected threshold as well as the abatement.

- **Probit Stage 2.** Denote the conditional performance as

$$\Pr\{y_{ij2}=1|y_{ij1}=1\}=\Phi(f_{ij}(\Theta_2)|y_{ij}=1) \tag{127}$$

where y_{ij2} is the dummy variable equal to 1 if the firm meets the target in CCAs, specificed as in the empirical section. The parameter Θ_2 is determined so that to maximize the conditional log likelihood

$$\mathcal{L}_2(\Theta_2)=\sum_{i=1}^{n}\{y_{ij}=1\}\big(y_{ij2}\ln\Phi(f_{ij}(\Theta_2)|y_{ij}=1)+(1-y_{ij2})\ln(1-\Phi(f_{ij}(\Theta_2)|y_{ij}=1)\big) \tag{128}$$

Recalling the latent variable y^*_{ij2} in the empirical section, one notes that by properties of the truncated normal disribution, it holds

$$\begin{cases} \mathbb{E}[y^*_{ij2}|y_{ij}=1]=\mathbb{E}[\delta^*_{ij}(\gamma)]-\bar{\delta}_j+\rho\sigma_2\Lambda_{ij} \\ Var[y^*_{ij2}|y_{ij}=1]=\sigma_2^2\Big(1-\rho^2[(\mathbb{E}[\tilde{z}_{ij}(\gamma,\beta)]-\bar{\delta}_j)\Lambda_{ij}+\Lambda^2_{ij}]\Big) \end{cases} \tag{129}$$

where Λ_{ij} is the inverse Mill's ratio evaluated in the threshold. From the expressions in (129), it follows that the conditional performance in (127) lies in between

$$\hat{f}_{ij}(\Theta_2)\approx\Big[\sigma_2^{-1}\big(\mathbb{E}_{ij}\hat{\delta}-\bar{\delta}_j\big)+\rho\hat{\Lambda}_{ij};\ \frac{\sigma_2^{-1}\big(\mathbb{E}\hat{\delta}_{ij}-\bar{\delta}_j\big)+\rho\Lambda_{ij}}{1-\rho^2[(\mathbb{E}\hat{z}_{ij}-\bar{\delta}_j)\hat{\Lambda}_{ij}+\hat{\Lambda}^2_{ij}]}\Big] \tag{130}$$

with $\Theta_2=\{\sigma_2,\rho\}$ where $\hat{\Lambda}_{ij},\mathbb{E}\hat{z}_{ij}$ and $\mathbb{E}\hat{\delta}_{ij}$ are estimated from the parameters $\hat{\gamma}$, $\hat{\beta}$ obtained in the first stage. The estimation process for $\Theta_2=\{\sigma_2,\rho\}$ follows similar steps as in (125) and (126) once the gradient and hessian $\nabla_{\Theta_2}f_{ij}(\Theta_2)$ and $\Delta_{\Theta_2}f_{ij}(\Theta_2)$ are determined. Denote $1/\sigma_2=\tilde{\beta}_2$, $v_{ij}=\big(\mathbb{E}\hat{\delta}_{ij}-\bar{\delta}_j\big)$ and $k_{ij}=[(\mathbb{E}\hat{z}_{ij}-\bar{\delta}_j)\hat{\Lambda}_{ij}+\hat{\Lambda}^2_{ij}]$, then

$$\begin{cases} \partial\tilde{\beta}_2 f_{ij}=\frac{v_{ij}}{1-\rho^2k_{ij}} \\ \partial\rho f_{ij}=\frac{\hat{\Lambda}_{ij}(1+\rho^2k_{ij})}{(1-\rho^2k_{ij})^2} \end{cases} \tag{131}$$

whereas

$$\begin{cases} \partial\tilde{\beta}_2\partial\tilde{\beta}_2 f_{ij}=0 \\ \partial\tilde{\beta}_2\partial\rho f_{ij}=\frac{2\rho v_{ij}k_{ij}}{(1-\rho^2k_{ij})^2} \\ \partial\rho\partial\rho f_{ij}=\frac{2\rho\Lambda_{ij}k_{ij}}{(1-\rho^2k_{ij})^2}+\frac{4\rho\Lambda_{ij}(1+\rho^2k_{ij})(1-\rho^2k_{ij})}{(1-\rho^2k_{ij})^4} \end{cases} \tag{132}$$